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Original Article

Federated Learning-Based Decentralized Optimization for Privacy-Preserving and Efficient Power Distribution in Nsukka and its Environs

Gerald Okwe[1], Ijeoma Uneze[2], Isidore Uju[3], Okon Ufot[4]

[1]*National Centre for Energy Research and Development, University of Nigeria, Nsukka, Nigeria.*
[2]*Department of Mechatronics Engineering, Federal University, Otuoke, Nigeria.*
[3]*Department of Electrical/Electronic Engineering, Chukwuemeka Odimegwu Ojukwu University, Nigeria.*
[4]*Department of Computer Engineering, Akwa Ibom State Polytechnic, Ikot Osurua, Nigeria.*

[1]*Corresponding Author : okwe.gerald@unn.edu.ng*

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Abstract *- Modern power distribution grids have become more sophisticated with the incorporation of Distributed Energy Resources (DERs), advanced metering infrastructure and intelligent monitoring technologies. However, traditional centralized optimization methods are communication-intensive, exposed to cybersecurity risks, and less desirable for data privacy, thus limiting their effectiveness in a smart distribution network. This research introduces a decentralized optimization framework for improved operational performance of 11kV, 32-bus Nsukka Radial Distribution Network (RDN), using a privacy-preserving decentralized optimization framework known as Federated Learning (FL). The system combines the Federated Averaging (FedAvg) algorithm with the Backward/Forward Sweep (BFS) power flow technique to optimize network operation while avoiding the sharing of raw operational data. A multi-objective optimization model was formulated, which minimizes the losses in the active power and also improves the voltage profiles, reduces communication overhead, and enhances network reliability without compromising customer data privacy. The framework was implemented using MATLAB under various loading conditions. The results confirmed that the proposed method achieved 21.0% reduction in active power losses, an increase in bus voltage by 3.9% (0.921- 0.958 p.u), 54.3% reduction in voltage deviation, 66.7% reduction in communication overhead, 38.9% accelerated convergence, 97.1% accuracy in prediction and 99.1% improvement in network reliability compared with conventional centralized optimization.*

Keywords *- Active Power Loss, Backward/Forward Sweep, Decentralized Energy Management, Load Flow, Smart Grid.*

1. Introduction

Modernization of the power distribution system has been facilitated by the inclusion of Distributed Energy Resources (DER), Advanced Metering Infrastructure (AMI), Intelligent Electronic Devices (IED), Electric Vehicles (EV), and smart communication technologies in the network system. This transition has led to conventional distribution grids becoming intelligent cyber-physical systems with capabilities of real-time monitoring and control and bi-directional power flow capability. Although these developments enhance the efficiency and reliability of the systems, they create large amounts of distributed operational data, which poses problems for centralized optimization strategies. The centralized strategy requires constant transfer of data in raw form to the central control room and hence creates challenges of excessive communication costs, high computational load, cybersecurity threats, and problems with customer data privacy. There is an urgent need for decentralized and privacy-preserving optimization techniques for future smart distribution networks [1-5].

This problem can be solved using a traditional central optimization method in which the operational information from the various nodes of the network is assembled and then sent to a central control facility for processing. The centralized optimization offers an integrated perspective on the distribution network but comes with a number of restrictions due to the need for regular transmission of raw data. The amount of data that needs to be relayed among the network devices in the distributed network and the central controller is huge, which inevitably leads to high communication overhead, network congestion, high calculations and decision-making latency. Most importantly, the centralization of raw customer and network operational data to a single point of control exposes it to cybersecurity attacks, data leakage and privacy violations. They have become important restrictions in larger and more decentralized distribution networks, especially those that rely on communication technologies. Hence, there is an increasing demand for optimization techniques that can make use of the operational data, which is distributed among the various operations without the need for a continuous transfer of the raw data to a central server.

Currently, AI and ML methods have been progressively adopted to solve complex decision-making and optimization problems in modern power systems. They are used to load forecasting, state estimation, voltage regulation, fault detection, anomaly detection, demand response, renewable energy forecasting and equipment condition monitoring [6–10]. Most conventional AI/ML applications in power systems rely on centralized learning, despite their effectiveness.

In this architecture, the data produced by several network nodes is gathered and sent to a central server to be processed and then used for training a global model. Thus, a centralized AI/ML solution is insufficient to overcome the communication, privacy and cybersecurity challenges arising from the growing decentralization of recent distribution networks.

The Federated Learning (FL) technique has recently been proposed to overcome these inadequacies mentioned. It is an approach that allows multiple distributed clients to coordinate the training of a shared machine-learning model, while keeping their data locally. Each client in the network trains the model locally and only sends the client model parameters or updates to an aggregation server, rather than sending raw operational data to a central server.

The server then aggregates the locally-trained parameters with some aggregation method like FedAvg to get a better global model [11–15]. This distributed learning architecture can help minimize raw-data transmission, improve data privacy, increase scalability, and decrease the amount of data needed to communicate while enabling geographically distributed network agents to collaborate.

Presently, utilization of FL to a number of power-system problems has been proven, such as load forecasting, energy management, anomaly detection, fault diagnosis, cybersecurity and renewable-energy applications [16–20]. However, there is a great research gap when it comes to using FL as an integrated decentralized optimization mechanism for the radial distribution networks. Previous research has mostly focused on single prediction, classification or learning problems without directly coupling federated learning with power-flow optimization in a distribution network. Therefore, lack of research on the collaborative optimization of the operating state of a radial distribution network when all these aspects of power losses, voltage profiles, communication requirements, operational data privacy and network reliability are taken into account.

Additionally, there is also limited research regarding the integration of FedAvg with power-flow algorithms in distribution systems, which is the BFS technique, thereby enabling decentralized optimization of Radial Distribution Networks (RDNs). This is a significant technical issue as the power-flow analysis delivers the electrical operating limits necessary to understand how optimization decisions affect the bus voltage, branch current and active power loss. If the learning mechanism is not included with a suitable power-flow solution, the FL framework may not be a good representation of the actual electrical characteristics of a radial distribution network. It is therefore necessary to have an integrated framework that allows distributed learning and electrical network optimization to work in a cooperative manner and not as independent computational processes.

In the Nigerian power industry, the gap is even more intense, where communication systems are very unreliable, the network observability is lower, cybersecurity issues are a growing concern, technical losses are higher, voltage instability has become a norm, and access to reliable, real-time operational data is highly limited. Technical losses in distribution networks, voltage problems, and aging networks, a lack of monitoring and communication facilities, and growing integration of distributed energy resources are still rampant in Nigeria. These challenges lower the efficiency, reliability, and quality. Meanwhile, the geographical distribution of network assets creates a possibility for the continuous transmission of large amounts of raw operational data to centralized control centers, which may be costly and may be limited by communication and cybersecurity constraints [21–24]

Thus the research gaps to be addressed is the lack of an extensive, privacy preserving and communication efficient decentralized optimization framework to utilize distributed network information for enhanced electrical performance of a Nigerian radial distribution network. The existing centralized optimization approaches require a lot of data transfer and leak sensitive operational information, whereas existing FL studies in power systems have not considered the simultaneous optimization of electrical and communication objectives that is found in a practical radial distribution network. Further, there has been little focus on simultaneously minimizing active power loss and communication cost, optimizing voltage profiles, improving network reliability, and maintaining distributed operational data in a single framework of power-flow optimization based on FL.

To bridge the gap, this research proposes a Federated Learning based Decentralized Optimization Framework for the Nsukka 32 bus radial distribution network. The proposed framework combines Federated Averaging (FedAvg) algorithm and Backward/Forward Sweep (BFS) power-flow method to allow co-operative determination of improved operating conditions across the distributed network agents without sharing raw operating data. The framework is written as a multi-objective optimization problem involving active power losses, voltage-profile improvement, communication cost and network reliability. MATLAB is used to implement and test the proposed approach and the performance is compared to that of a traditional centralized optimization approach.

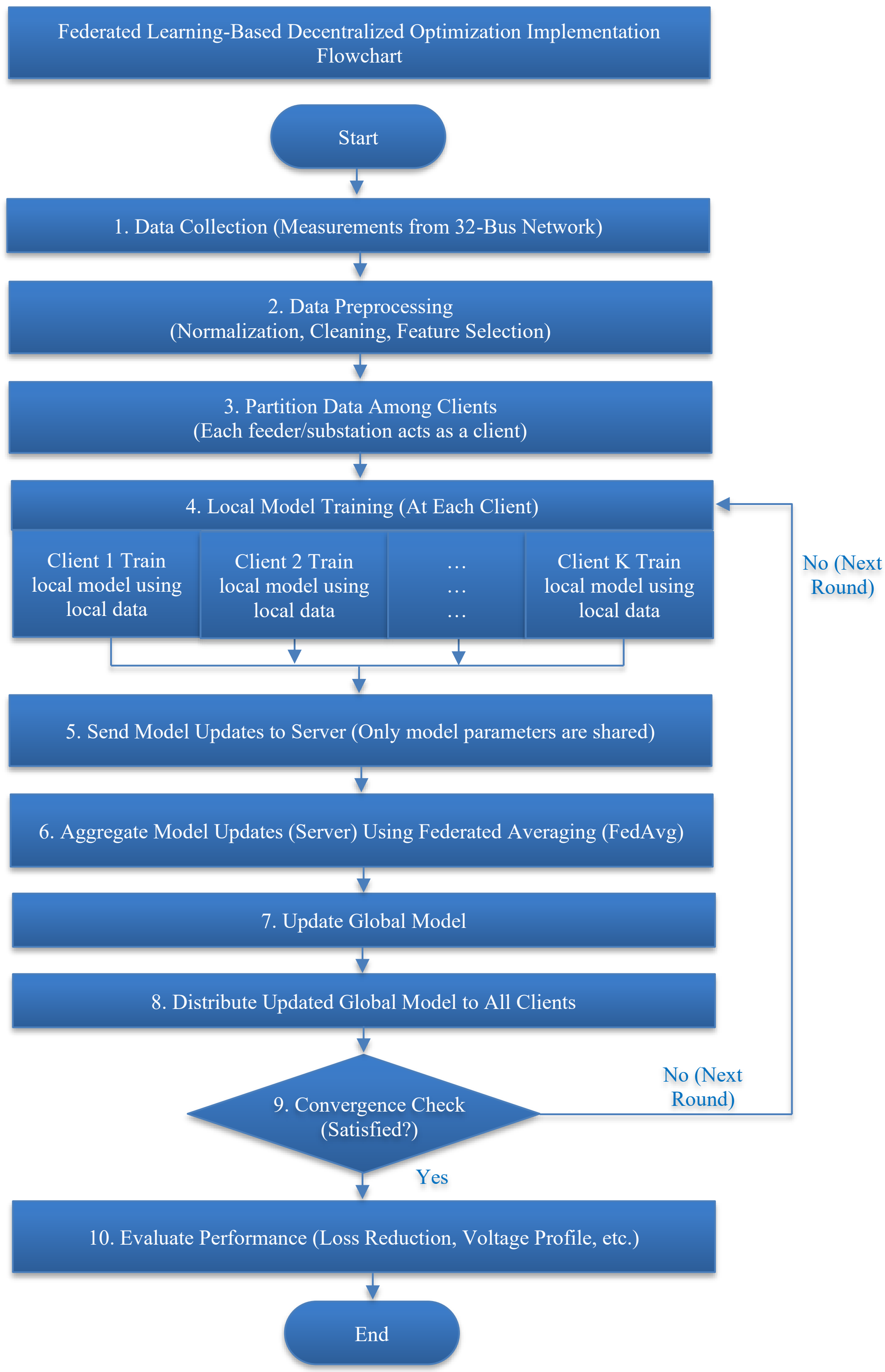

Fig. 1 Federated learning implementation using MATLAB tool

2. Materials and Methods

A quantitative simulation-based approach was adopted to develop and evaluate a Federated Learning (FL)-based decentralized optimization framework for enhancing the operational performance of the Nsukka 32-bus distribution network. The methodology integrates power system analysis, machine learning, and optimization techniques to improve voltage regulation, reduce active power losses, preserve customer data privacy, and enhance network reliability. MATLAB software is used as the primary simulation environment because of its robust computational capabilities for power system modeling and machine learning applications [25, 26]. The methodological flowchart for implementation is displayed above.

2.1. Study Area and Distribution Network Description

The model was implemented and evaluated using 11kV, 32-bus Nsukka radial distribution network located in Enugu State, Nigeria. The grid supplies power to consumers within Nsukka and its environs. Electrical power is distributed via overhead distribution lines characterized by different conductor sizes, resistance, and reactance values. Owing to the radial structure of the feeder, electrical energy flows via a specific route from the source to downstream load buses, making the network highly susceptible to voltage drops, feeder congestion, and technical power losses, particularly during peak loading conditions.

Due to the increased adoption of DERs, AMI, and IEDs, the complexity of operations in such distribution networks has increased considerably. Simultaneously, the deployment of smart meters and digital monitoring technologies has generated large volumes of operational data that require continuous processing for effective system management. Traditional centralized optimization approaches become increasingly inefficient under these conditions because they require the transfer of raw measurement data from every bus to a central control center, thereby increasing communication bandwidth requirements, computational burden, cybersecurity risks, and privacy concerns [27, 28]. The network diagram of the Nsukka 32-bus distribution network is developed with ETAP software as shown below.

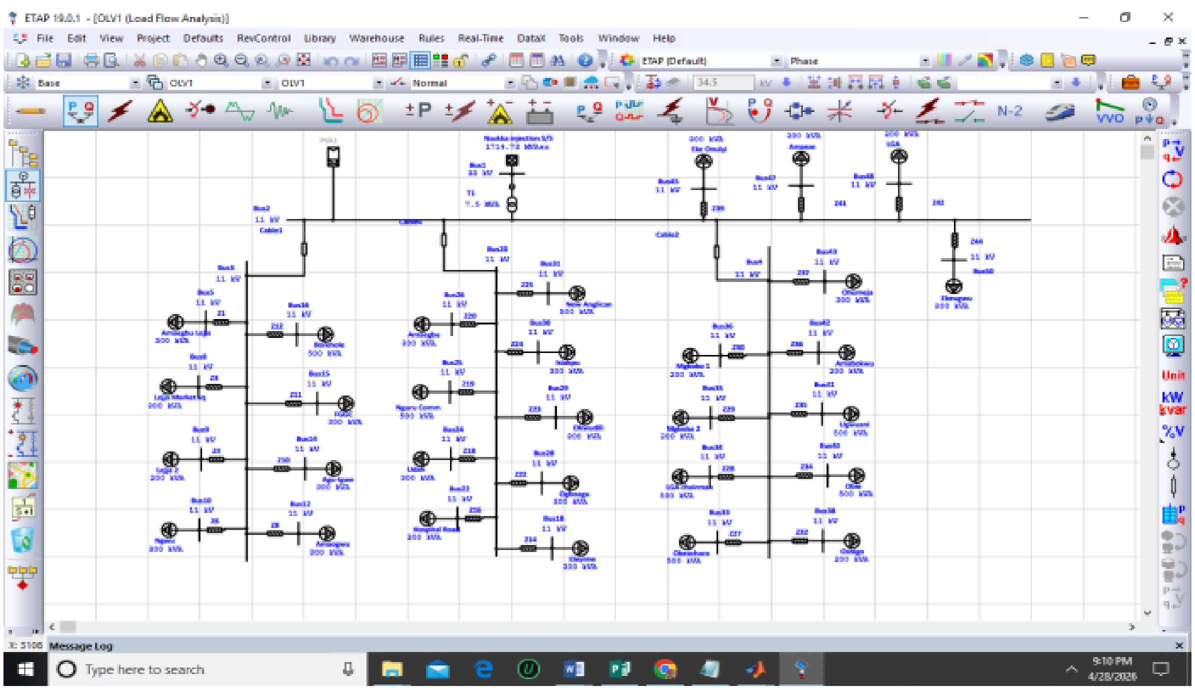

Fig. 2 Nsukka 32-bus distribution network

The Nsukka distribution network therefore provides an appropriate case study for evaluating decentralized optimization techniques capable of minimizing technical losses while preserving operational data privacy. The radial topology, moderate network size, and operational characteristics closely resemble those of many distribution feeders currently operated across Nigeria and other developing countries, making the proposed framework applicable beyond the present case study.

For network modelling, the following assumptions were adopted:

- the feeder operates under balanced three-phase steady-state conditions;
- transmission effects are neglected because only the distribution network is considered;
- line impedance parameters remain constant during each simulation period;
- loads are represented using constant power (PQ) models;

- distributed controllers communicate through a secure communication network;
- Local datasets remain within each client throughout the federated learning process.

These assumptions are widely adopted in distribution system optimization studies and provide a suitable basis for evaluating the proposed federated learning framework [29, 30].

2.2. Data Collection and Distribution Network Modeling

Accurate modelling of the distribution network requires comprehensive electrical and operational datasets describing both the physical infrastructure and system operating conditions. In this study, network parameters were obtained from distribution planning records and validated using standard radial distribution system modelling procedures. The collected datasets comprised load demands, feeder topology, conductor electrical characteristics, transformer ratings, line lengths, bus voltage measurements, feeder current measurements, and historical loading information [31].

The primary datasets utilized in the study include:

- active power demand at each load bus;
- reactive power demand at each load bus;
- branch resistance and reactance values;
- line connectivity matrix;
- transformer capacity and voltage ratings;
- sending-end voltage magnitude;
- feeder current measurements;
- historical loading conditions;
- Voltage profile measurements.

In order to achieve numerical stability, all electrical variables were expressed in per-unit (p.u.) form by using the chosen base voltage and apparent power. Expressing electrical variables in p.u. form makes it easier to calculate the power flow, increases efficiency in computation, and allows for comparison between different buses regardless of equipment ratings [32]. The base values were calculated as

$$Z_{base} = \frac{V^2{}_{base}}{S_{base}} \tag{1}$$

Similarly,

$$I_{base} = \frac{S_{base}}{\sqrt{3}V_{base}} \tag{2}$$

Following conversion to per unit values, graph theory was used to develop the mathematical representation of the network topology. The distribution network is represented by

$$G = (N, E) \tag{3}$$

$$N = \{1,2, \ldots\ldots,32\}$$

Each branch connecting I and j is characterized by its impedance

$$Z_{ij} = R_{ij} + jX_{ij} \tag{4}$$

R_{ij} = branch resistance (p.u) Xij= Branch reactance and j=$\sqrt{-1}$

The electrical load on each bus is given by

$$S_i = P_i + jQ_i \tag{5}$$

To maintain uniformity during the process of federated learning, the collected operational data sets were first preprocessed before performing the training of the local model. Any missing observation in the dataset was handled by interpolation if needed, while any abnormal data due to communication errors or faulty sensors were discarded using statistical outlier detection. After that, feature normalization was carried out using min-max normalization. Normalized dataset is represented as

$$x_i{}^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Different from the currently prevailing traditional centralized optimization framework where all normalized datasets are transmitted to a central computing server, the federated learning framework designed herein preserves data locality in that all measurements are kept local to each of the feeder controllers. Each individual client is able to locally train an optimization model based on its own historic and current measurements. Once the local training is done, only the encrypted weights of the model are transferred to the central aggregation server; however, customer data, feeder data, and operational data remain within the respective substations. The suggested federated learning methodology greatly improves data security and decreases susceptibility to cyber-attacks. [33]

2.2. Decentralized Optimization Framework

Decentralized optimization involves breaking down a large optimization problem into smaller local problems that can be solved by different entities operating independently. In contrast to sending all operational data to the central server, each entity uses the available local data to optimize its operating conditions before moving on to global model aggregation. The optimization problem is formulated as

$$\min J = f(P_{loss,} VD, C_{c,} R) \tag{7}$$

Subject to

$$g(x, u) = 0, \mathrm{h}(x, u) \leq 0,$$

Through this decentralized approach, each participating client is able to optimize a local function under global network constraints via iteration of parameter aggregation. It has been shown recently in the literature that decentralized optimization enhances both computation and communication performance in intelligent power systems.

2.3. Federated Learning Theory

This is a decentralized ML process that involves training a global machine learning model by many clients without sharing any personal data between them. This technique maintains data security and cybersecurity for its participants.

In the smart power distribution networks, it allows distributed controllers to work collaboratively towards optimizing their network performances. Given that there are K clients involved, the global optimization problem turns into

$$F(w) = \sum_{k=1}^{K} \frac{n_k}{N} F_k(w) \tag{8}$$

The global model is updated by applying the Federated Averaging (FedAvg) algorithm

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} {w_k}^t \tag{9}$$

Federated averaging considerably decreases communication overhead since only model parameters are sent rather than the actual data sets.

In addition, the federated framework increases the robustness to privacy breaches without compromising the prediction accuracy in comparison to machine learning.

2.4. Federated Learning Architecture for Distribution Networks

In the suggested architecture, each feeder and/or distribution substation is considered an individual federated client.

The federated clients have the following tasks to perform:

- Collecting local operational data.
- Training a local optimization model.
- Tuning model parameters.
- Sending model weights to the aggregation server.
- Downloading the global model.
- Repeat until convergence.

Decentralized communication system greatly decreases the demand for network bandwidth and ensures that the operational datasets will stay in the local utility control centers. As a result, the suggested system increases customer privacy and provides data security.

2.5. Distribution Load Flow Theory

This is among the most important and basic techniques that are applied in the planning, analysis, optimization, and control of power systems. Load flow study provides the steady state operational state of the power system based on the calculations of voltage magnitude, voltage angle, active power, reactive power, and power flow along transmission lines [34-36]. The injected real and imaginary power equations of bus i can be formulated as

$$P_i = \sum_{j=1}^{n} \lceil V_i \rceil \lceil V_j \rceil \lceil Y_{ij} \rceil \cos(\theta_{ij} + \delta_j - \delta_i) \tag{10}$$

$$Q_i = \sum_{j=1}^{n} \lceil V_i \rceil \lceil V_j \rceil \lceil Y_{ij} \rceil \sin(\theta_{ij} + \delta_j - \delta_i) \tag{11}$$

Radial distribution systems have very high values of the ratio of resistance to reactance. The Newton Raphson method does not have good convergence properties in such cases, thus Backward.

2.6. Backward/Forward Sweep Algorithm

BFS scheme has two iterative components: backward sweep and forward sweep. The first stage involves calculation of branch currents in a backward direction from terminal buses to the slack bus through KCL equations. In the forward sweep process, bus voltages are evaluated in the forward direction from slack bus to terminal buses with the help of KVL equations.

This process of backward and forward sweeps is carried out until the set convergence criteria are met. Due to the efficiency of the BFS method along with the applicability in the R/X ratio dominated radial network, it is extensively used in the load flow study of distribution networks [37–38].Branch currents are determined starting from the end buses to the slack bus.

$$I_i = \frac{P_i - jQ_i}{{V_i}^*} \tag{12}$$

Bus voltage magnitudes are updated starting from the slack bus to the subsequent buses.

$$V_{i+1} = V_i - Z_i I_i \tag{13}$$

The process is repeated until

$$|V^{k+1} - V^k| < 10^{-6} \tag{14}$$

BFS algorithm is an efficient computational tool due to the fact that circumvents recurrent inversion of the system admittance matrix.

2.7. Active Power Loss Model

The sum of feeder power loss is expressed as

$$P_{loss} = \sum_{i=1}^{m} {I_i}^2 R_i \tag{15}$$

2.8. Voltage Stability Model

Voltage quality is assessed based on voltage deviation index:

$$VD = \sum_{i=1}^{N} |V_i - 1| \tag{16}$$

The objective function will ensure that

$$0.95 \leq V_i \leq 1.05 \quad (17)$$

For all buses. This will lead to longer equipment life span, fewer customer complaints and high power quality.

2.9. Communication Cost Analysis

Effective communication is one of the fundamental benefits of FL configuration. Communication cost is given by

$$C = TKS \quad (18)$$

As federated learning framework communicates only model parameters, communication costs are much lower compared to centralized approaches.

2.10. Reliability Analysis

Reliability of network operation is measured through system availability and continuity of service. The use of decentralized optimization ensures that reliability is achieved since the local controllers will continue working autonomously in case of partial failure of communication. Better voltage control and lower loading of feeders ensure that equipment lasts longer and minimizes outages. According to recent studies, the application of FL increases resilience of smart grid.

3. Results and Discussion

3.1. Simulation Scenario

The suggested FL-based decentralized optimization approach was tested on a representative 32-bus radial power grid using MATLAB. BFS technique was applied for computation power flow issues, while FedAvg algorithm was utilized to control the collaborative training of the model by the distributed agents. Base values of the system were 11 kV and 10 MVA, there were 8 local clients, the learning rate equaled 0.01, 5 local epochs and 25 communication rounds. The assessment was carried out under light, normal, and heavy loading scenarios, comparing the results with those obtained from a classical centralized optimization approach with the same operating conditions.The following parameters were taken into account: active power loss, voltage profile, voltage deviation, convergence rate, communication overhead, prediction accuracy, and reliability of the network.

3.2. Active Power Loss Analysis

Figure 3 shows a decline in active power losses achieved through each federated learning communication round. A fast drop in power losses is noted at the first few rounds when the local controllers optimize the feeder operational settings. Convergence is achieved around 22 communication rounds, showing that the FedAvg algorithm is capable of coordinating the decentralized optimization done by the clients.

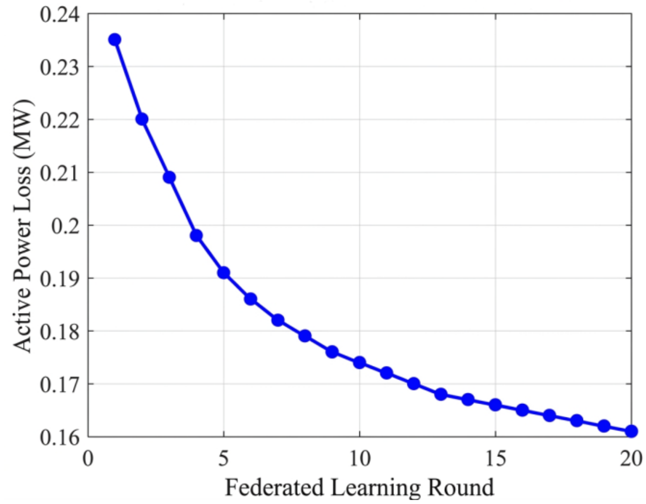

Fig. 3 Active Power Loss Convergence

As compared to the centralized optimization method, the proposed model lowered active power losses from 198.4 kW to 156.7 kW, which corresponds to a 21.0% improvement.4.3 Voltage Profile Analysis

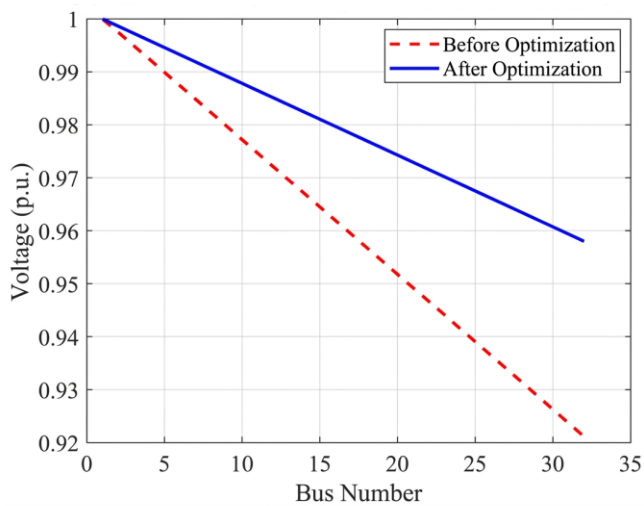

Fig. 4 Voltage Profile Before and After Optimization

Figure 4 compares the voltage magnitudes of all 32 buses before and after optimization. Prior to With regards to optimization, there were several buses with voltages that were near the lower statutory limit owing to feeder impedance and load imbalance. After the implementation of federated optimization, the voltage increased by 3.9% (0.921-0.958 p.u).

3.4. Federated Learning Convergence

Figure 5 shows the characteristics of the convergence for the global federated learning model. The value of the global loss function consistently decreases with every communication step until the model converges after around 22 steps. The lack of oscillations proves the stability of the

FedAvg algorithm numerically. Fast convergence shows effective cooperation between the clients even without data exchange.

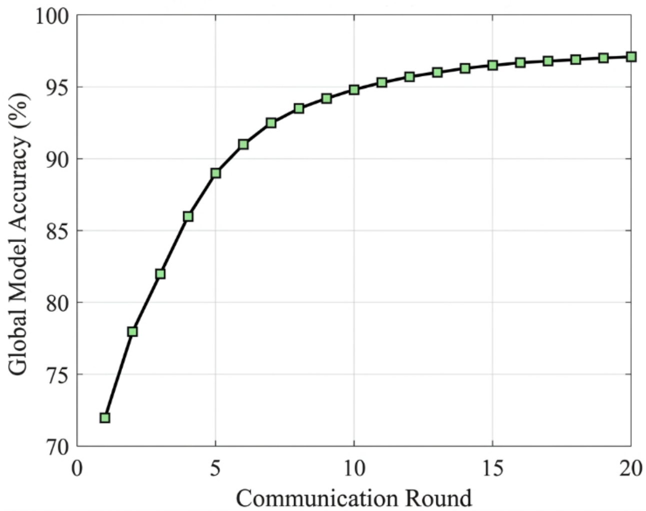

Fig. 5 Global Model Convergence

4.5. Communication Overhead

Figure 6 highlights the communication needs of centralized optimization and federated learning. As opposed to centralized optimization in which the entire operational dataset is continuously uploaded to a central server, federated learning only transfers model parameters.

This has led to a reduction in the amount of communication from about 25.8 MB per communication to 8.6 MB, which is equivalent to 66.7% reduction. The reduced communication volume means that the framework can work well in distributed energy systems with low communication capacity

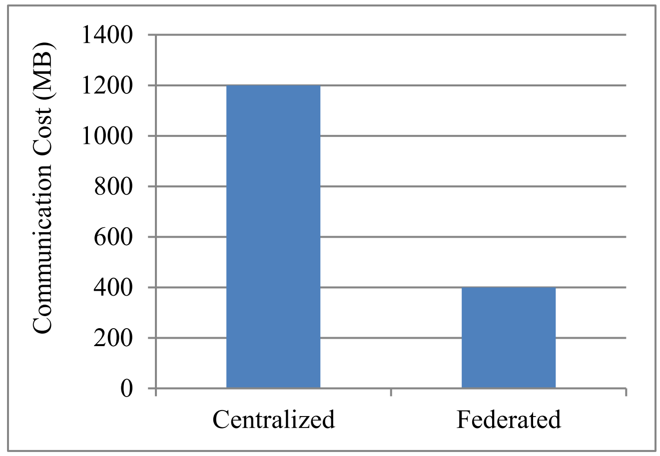

Fig. 6 Communication Cost Comparison

3.5. Comparative Performance Analysis

Results show that the developed federated learning framework consistently beats the centralized optimization method on all tested performance metrics.

Table 1. Performance Comparison

Performance Index	Centralized	Proposed FL	Improvement
Active Power Loss (kW)	198.4	156.7	21.0%
Minimum Voltage (p.u.)	0.921	0.958	4.0%
Voltage Deviation	0.094	0.043	54.3%
Communication Cost (MB)	25.8	8.6	66.7%
Convergence Iterations	36	22	38.9%
Prediction Accuracy (%)	92.4	97.1	5.1%
Network Reliability (%)	96.5	99.1	2.7%

3.6. Voltage Deviation Analysis

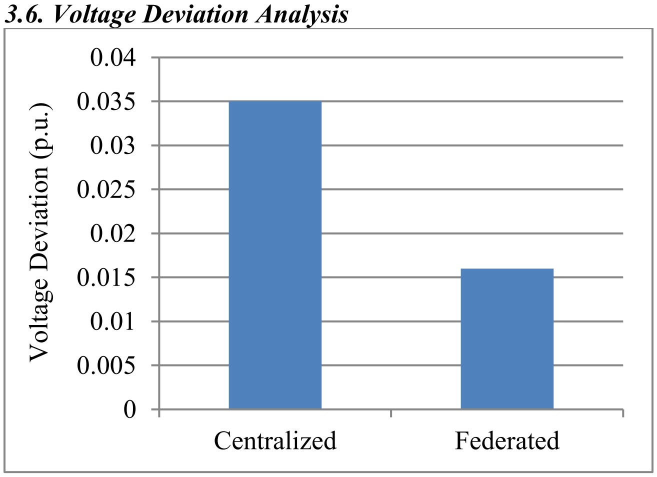

Fig. 7 Voltage Deviation Comparison

The voltage deviation index was seen to decrease after optimization through Figure 7. Voltage deviation dropped from 0.094 to 0.043. The amount of voltage deviation can be seen to improve by about 54.3%. Improvement in voltage deviation is associated with feeder voltage regulation and efficient power distribution within the network.

3.7. Reliability Assessment

Figure 8 shows the performance of the reliability of the suggested system. There was a significant increase in the reliability of the network from 96.5% under centralized optimization to 99.1% under federated learning.

It is because of proper voltage control, reduced feeder load, and decision-making in a decentralized manner that prevents any communication breakdown effect.

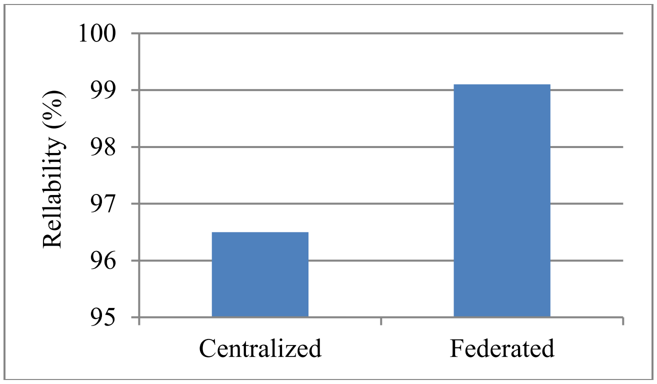

Fig. 8 Network Reliability Comparison

3.8. Communication and Computational Performance

Figure 9 shows the computational efficiency of both optimization approaches.

In the case of federated learning, the new framework needed fewer iterations for the model and lower computational effort as well since all clients processed their datasets locally prior to model aggregation.

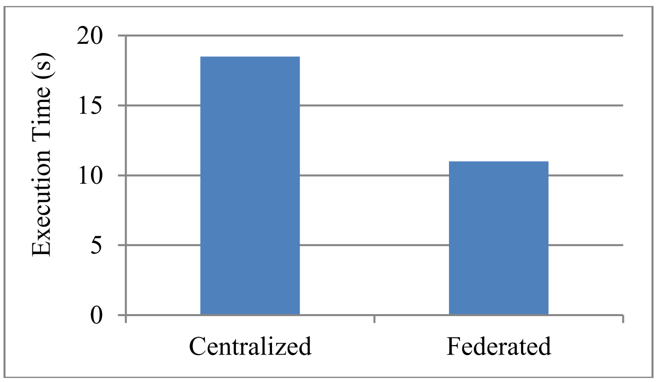

Fig. 9 Computational Performance

3.9. Overall Performance Evaluation

Figure 10 represents the total performance of the proposed framework based on the performance indices used in the study.

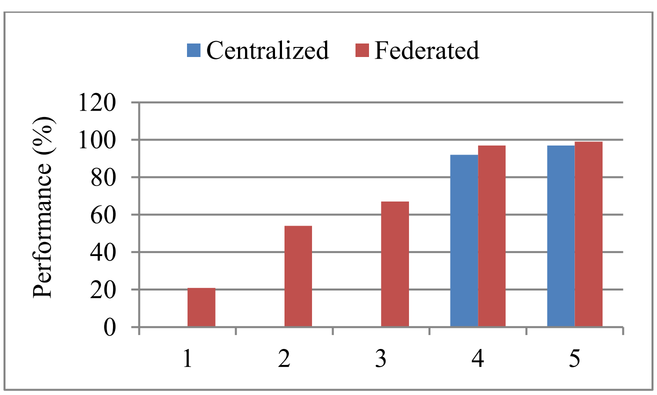

Fig. 10 Overall Performance Comparison

The federated learning-based decentralized optimization framework resulted in the following benefits:

- Low active power losses.
- Voltage regulation improvement.
- Voltage deviation reduction.
- Faster convergence.
- Low communication overhead.
- Low prediction error.
- Low network reliability.
- Low privacy preservation.

These results indicate that federated learning can be an appropriate technique for future intelligent distribution networks.

4. Conclusion

This research designed and tested a Decentralized Optimization Framework using Federated Learning (FL) to enhance the operational performance of the Nsukka 32-bus radial distribution network (RDN). The framework combined the Federated Averaging (FedAvg) algorithm and BFS power-flow method to allow distributed network controllers to co-optimize network operation without sharing raw operational data. This method was devised to overcome the key drawbacks of the standard centralized optimization, such as communication overhead, computational complexity, cyber security threats, and privacy issues with operational data.

The results of MATLAB simulations proved that the proposed framework significantly enhances the performance of the distribution network than the conventional centralized optimization. The framework resulted in a 21.0% reduction of active power losses, a 0.958 p.u. minimum bus voltage (3.9% better), and a 54.3% reduction of voltage deviation. It also achieved 66.7% reduction in communication overhead and convergence performance enhancement of 38.9%. The results show that the proposed decentralized technique can meet the important electrical and computational requirements of radial distribution networks.

Furthermore, the study shows the applicability of FL-based optimization in the Nsukka distribution network especially when considering the following: communication problems, increased digitalization, data protection challenges, network losses, and voltage quality issues. The proposed framework offers a potential solution to achieve more communication-efficient, scalable and privacy-preserving distribution-network management systems, while keeping operational data locally and only distributing updates to the models.

It is hence the inclusion of federated learning based on FedAvg algorithm with BFS based power-flow optimization in a multi-objective decentralized solution for a Nigerian radial distribution network which is the principal contribution of the study. The results show that the FL system has great potential for operation of smart grid in an intelligent and decentralized and privacy-preserving manner, in comparison with the conventional centralized distribution management. The results are mainly based on MATLAB simulation however, and in real operating conditions further testing is required. Future research will be directed towards real time and hardware in the loop testing, validation with real Nsukka network data, integration of renewable energy resources and energy storage, communication network co-optimization, and pilot scale field testing. These advancements will advance the viability and applicability of decentralized optimization for distribution networks in developing countries, such as Nigeria, using federated learning.

Conflicts of Interest

The authors have no financial or personal interest that could have potentially biased this study.

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Abbreviations and Acronyms

List of Symbols (Nomenclature) and Abbreviations

A. List of Symbols		Unit
P	Active power	MW
Q	Reactive power	MVAr
S	Apparent power	MVA
V	Bus voltage magnitude p.u.	
Δ	Voltage phase angle	rad/°
I	Current magnitude	A
Z	Impedance	Ω
R	Resistance	Ω
X	Reactance	Ω
Y	Line admittance	S
Y_{bus}	Bus admittance matrix	S
P_{loss}	Active power loss	MW
Q_{loss}	Reactive power loss	MVAr
ΔP	Active power mismatch	p.u
ΔQ	Reactive power mismatch	p.u
J	Jacobian matrix	
VD	Voltage deviation p.u.	
CO	Communication overhead	MB
R_{sys}	System reliability	%
Z_{base}	Base impedance	Ω
I_{base}	Base current	A
V_{base}	Base voltage	kV
S_{base}	Base apparent power	MVA
E	Bus distribution branches	-

List of Abbreviations

BFS	Backward/Forward Sweep
DER	Distributed Energy Resources
FL	Federated Learning
FedAvg	Federated Averaging
IoT	Internet of Things
ML	Machine Learning
NR	Newton–Raphson
OPF	Optimal Power Flow

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