

Federated Learning on Embedded Sensor Networks

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Abstract

Embedded sensor networks are widely used in smart cities, healthcare monitoring, industrial automation, agriculture and environmental sensing. These networks generate huge amount of data at the edge devices which are usually resource constrained in power, memory and computation. Traditionally, data from sensors is sent to cloud servers for training machine learning models, but this leads to privacy issues, high communication cost, and latency. Federated Learning (FL) is a new distributed learning approach where model training happens locally on devices and only model parameters are shared instead of raw data. This concept is highly suitable for embedded sensor networks where privacy, bandwidth and energy efficiency are critical. This paper reviews the concept of federated learning applied to embedded sensor nodes, discusses system architecture, communication models, challenges, energy constraints, security aspects, and recent applications. Tables and figures are provided to show comparison with traditional centralized learning and architecture of FL-based sensor network. The paper also highlights open research problems and future directions in this area.

Keywords: *Federated learning, embedded systems, sensor networks, edge AI, distributed learning, privacy preservation, IoT.*

1. INTRODUCTION

Embedded sensor networks consists of many small sensor nodes deployed in environment to collect physical parameters such as temperature, pressure, humidity, vibration, ECG signals, sound and images. These nodes are typically battery powered and have limited processor and

memory. With advancement of Internet of Things (IoT), these sensors are connected to internet and generate continuous data streams.

Machine learning techniques are increasingly used to analyze this sensor data for prediction, classification and anomaly detection. However, sending raw data from thousands of nodes to central cloud is not always feasible. It consumes large bandwidth, introduces delay, and most importantly raises privacy concerns especially in healthcare and surveillance applications.

Federated Learning (FL) was introduced to solve this problem by training a global model across distributed devices without transferring raw data. Each device trains a local model using its own data and only shares model updates with a central aggregator. This approach is very promising for embedded sensor networks.

2. OVERVIEW OF FEDERATED LEARNING

Federated Learning (FL) is a distributed machine learning paradigm in which many edge devices such as embedded sensor nodes collaboratively train a common global model without sharing their raw data. The key idea is **“bringing the model to the data instead of bringing data to the model.”** This approach is highly suitable for embedded sensor networks where privacy, bandwidth, and energy limitations are major concerns.

The concept was first introduced by Google in 2017 to train mobile keyboard prediction models without collecting user typing data. Since then, FL has been extended to IoT devices, wearable sensors, industrial nodes, and smart city infrastructures.

In traditional centralized learning, all sensor data is transmitted to a central server where the model is trained. In federated learning, each device performs local training using its own dataset and only shares model parameters (such as weights or gradients) with a central coordinating server.

2.1 Working Principle of Federated Learning

Federated learning operates in iterative communication rounds between a central server (or edge gateway) and multiple sensor devices.

Step	1:	Global	Model	Initialization
The federated server initializes a global machine learning model. This could be a neural network, decision tree, regression model, or any suitable ML model depending on the application. The initial model may be randomly initialized or pre-trained.				

Step 2: Distribution of Model to Sensor Nodes

The server sends the current global model parameters to a subset of participating sensor nodes. Not all nodes participate in every round to save communication cost and energy.

Step 3: Local Training at Sensor Nodes

Each selected sensor node trains the received model using its locally stored data. This training is done for a few epochs using local computational resources. Since data remains inside the device, privacy is preserved.

Mathematically, each node updates the model parameters by minimizing its local loss function:

$$w_i = w - \eta \nabla L_i(w) \quad w_{i+1} = w - \eta \nabla L_i(w)$$

where:

w = global model weights,
 η = learning rate,
 L_i = local loss function of node i .

Step 4: Uploading Model Updates

After local training, nodes send only the updated weights (or gradients) back to the server. No raw sensor data is transmitted.

Step 5: Aggregation Using Federated Averaging (FedAvg)

The server aggregates all received model updates to create a new global model. The most common aggregation method is **Federated Averaging**, defined as:

$$w_{global} = \sum_{i=1}^N \frac{n_i}{n} w_i \quad w_{global} = \frac{1}{n} \sum_{i=1}^N n_i w_i$$

where:

n_i = number of data samples at node i ,
 n = total samples across all nodes.

This ensures nodes with more data have higher influence.

Step 6: Redistribution of Updated Global Model

The updated global model is again distributed to sensor nodes for the next round of training.

This cycle repeats for many rounds until the model converges to desired accuracy.

2.2 Key Characteristics of Federated Learning

- **Data Locality:** Sensor data never leaves the device.
- **Privacy Preservation:** Sensitive data like medical or environmental data remains secure.
- **Reduced Bandwidth Usage:** Only model parameters are transmitted.

- **Scalability:** Thousands of nodes can participate.
- **Fault Tolerance:** Some nodes may drop out without affecting overall training.

2.3 Types of Federated Learning

Depending on data distribution across devices, FL can be classified into:

1. **Horizontal FL (Sample-based):**
Devices share same feature space but different data samples. Common in sensor networks.
2. **Vertical FL (Feature-based):**
Devices share same samples but different features.
3. **Federated Transfer Learning:**
Used when both samples and features differ.
For embedded sensor networks, **Horizontal FL** is most common.

2.4 Communication Rounds and Convergence

The performance of federated learning depends on:

- Number of communication rounds
- Number of participating nodes per round
- Local training epochs
- Quality of local data (often non-IID)

Too many rounds increase energy usage, while too few rounds reduce accuracy. Hence, a balance is required in embedded systems.

2.5 Why Federated Learning Fits Sensor Networks

Sensor networks are distributed by nature, produce continuous data, and operate under strict energy and bandwidth constraints. FL leverages these characteristics by:

- Performing computation locally
- Minimizing wireless transmission
- Allowing collaborative intelligence without central data collection

Thus, federated learning becomes a natural solution for intelligent embedded sensor deployments.

3. EMBEDDED SENSOR NETWORK CHARACTERISTICS

Embedded sensor networks are formed by large number of small, intelligent sensor nodes deployed across physical environments to monitor real-world parameters. These nodes are usually built around microcontrollers, low-power radios, sensors, and limited memory. Their design constraints and operating conditions are very different from traditional computing systems, and these characteristics directly influence how machine learning—especially federated learning—can be implemented on them.

The following features define embedded sensor networks.

3.1 Limited Power Availability

Most sensor nodes are battery operated or energy harvested (solar, vibration, thermal). Replacing batteries frequently is not practical, especially in remote areas like forests, farms, pipelines, or industrial plants.

- Communication consumes more energy than computation.
- Continuous data transmission to cloud quickly drains battery.
- Duty cycling (sleep–wake scheduling) is common.

This makes **local computation with minimal communication**, as in federated learning, more suitable.

3.2 Low Computational Capability

Sensor nodes typically use microcontrollers such as ARM Cortex-M, AVR, or ESP32 with:

- Clock speeds in MHz range
- RAM in KBs or few MBs
- No GPU or heavy processing unit

These limitations restrict the size and complexity of ML models that can run on nodes. Lightweight models, TinyML, quantized networks, and optimized training routines are required.

3.3 Limited Memory and Storage

Embedded nodes cannot store large datasets or complex models.

- Flash storage is limited
- RAM is very small for buffering data
- Models must be compressed and efficient

This constraint motivates the use of **small local datasets** and incremental learning during federated rounds.

3.4 Wireless Communication Constraints

Sensor nodes communicate using low-power wireless protocols such as:

- ZigBee
- LoRaWAN
- BLE
- Wi-Fi (in some cases)

These networks have:

- Low bandwidth
- Packet loss
- Limited range
- High latency in some cases

Hence, transmitting raw data is inefficient, while sending small model updates is feasible.

3.5 Distributed and Large-Scale Deployment

Sensor nodes are spread over large geographical areas:

- Agricultural fields
- Smart cities
- Industrial plants
- Environmental monitoring regions

This distributed nature aligns well with federated learning where nodes collaboratively train a model without centralized data collection.

Feature	Description
Limited power	Battery operated nodes, energy saving is critical
Low computation	Microcontrollers with small RAM and CPU
Wireless communication	Uses ZigBee, LoRa, WiFi, BLE etc
Distributed topology	Nodes placed over large area
Real time sensing	Continuous data generation

These characteristics makes centralized learning difficult and federated learning more attractive.

4. ARCHITECTURE OF FEDERATED LEARNING IN EMBEDDED SENSOR NETWORKS

The architecture of Federated Learning (FL) in embedded sensor networks is designed to distribute intelligence across many low-power sensor nodes while coordinating learning through edge gateways and a central federated server. Unlike traditional cloud-centric AI systems, this architecture pushes computation toward the edge and minimizes raw data movement across the network.

A typical FL-enabled sensor network follows a **three-tier architecture**:

1. **Sensor Node Layer (Edge Devices)**
2. **Edge Gateway Layer (Fog/Edge Aggregator)**
3. **Federated Server Layer (Cloud or Control Center)**

4.1 Sensor Node Layer (Local Training Layer)

This is the lowest layer consisting of embedded sensor nodes deployed in the field.

Components of a sensor node:

- Sensors (temperature, ECG, vibration, gas, etc.)
- Microcontroller (ARM Cortex-M, ESP32, AVR)
- Memory (RAM/Flash)
- Wireless module (LoRa, ZigBee, BLE, Wi-Fi)
- Power source (battery/energy harvesting)

Role in FL architecture:

- Collect real-time environmental or physiological data
- Store small local dataset temporarily
- Receive global model from server
- Perform **local training** using TinyML or lightweight ML libraries
- Send only updated model parameters back

Local training reduces communication and preserves privacy.

4.2 Edge Gateway Layer (Intermediate Aggregation Layer)

Edge gateway acts as bridge between many sensor nodes and the central server. It may be a Raspberry Pi, industrial PC, or IoT gateway.

Functions of edge gateway:

- Collect model updates from nearby sensor nodes
- Perform **pre-aggregation** (hierarchical FL)
- Handle unreliable connectivity from sensors
- Provide temporary storage and preprocessing
- Manage security (encryption, authentication)
- Forward aggregated updates to federated server

This layer reduces the communication burden on the cloud and improves scalability.

4.3 Federated Server Layer (Global Coordination Layer)

This is the top layer, typically hosted in cloud or central control station.

Functions of federated server:

- Initialize global ML model
- Select subset of sensor nodes for each round
- Aggregate model updates using FedAvg or other algorithms
- Monitor convergence and performance
- Redistribute updated global model
- Maintain logs, security policies, and scheduling

The server never accesses raw sensor data.

4.4 Data and Model Flow in the Architecture

The learning process flows as follows:

1. Server sends global model → edge gateways → sensor nodes.
2. Sensor nodes train model locally with sensed data.
3. Nodes send updated weights → gateway.
4. Gateway aggregates and forwards → server.
5. Server computes new global model.
6. Updated model redistributed for next round.

This cycle continues for multiple communication rounds.

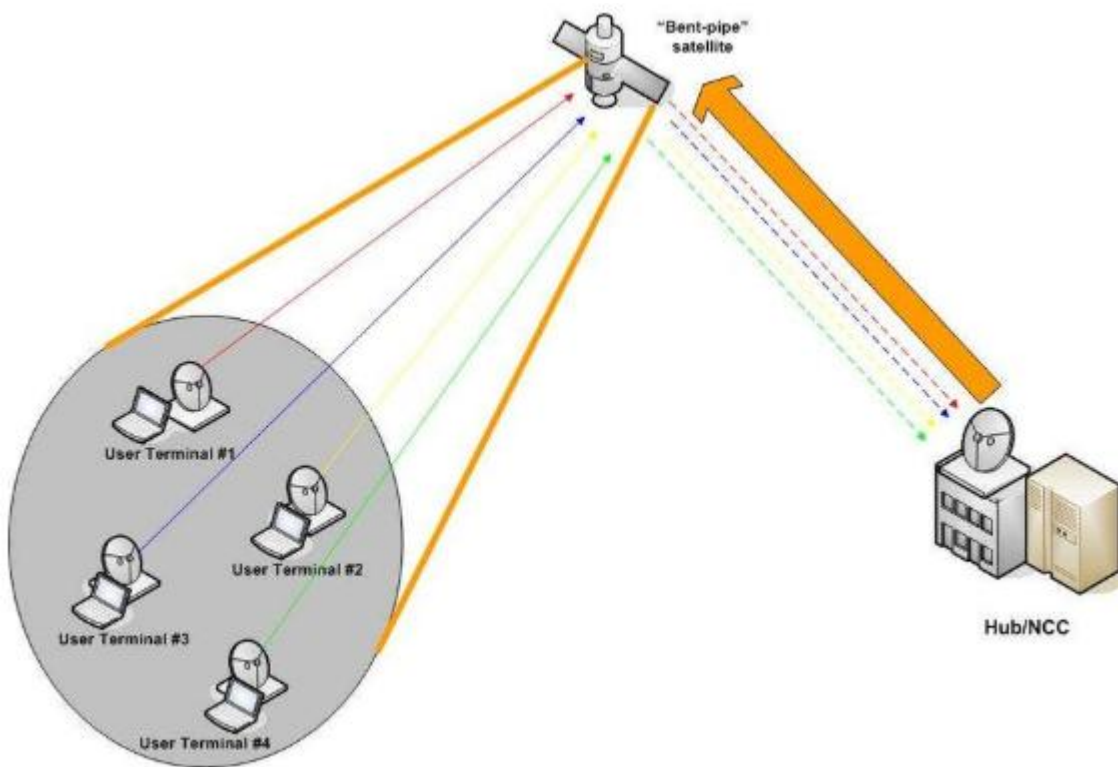


Figure 1 shows typical architecture.

Sensor nodes perform local training. Edge gateway or base station collects model updates and forwards to central federated server.

Sometimes aggregation can also be done at edge gateway to reduce cloud communication.

5. COMPARISON: CENTRALIZED VS FEDERATED LEARNING

Parameter	Centralized Learning	Federated Learning
Data transfer	Raw data sent to cloud	Only model weights sent
Privacy	Low	High
Bandwidth usage	Very high	Moderate
Energy consumption	High	Lower
Latency	High	Low
Scalability	Limited	High

6. COMMUNICATION MODELS IN FL SENSOR NETWORKS

Communication is major cost in sensor nodes.

- **Synchronous FL:** All nodes send updates together. Simple but slow.
- **Asynchronous FL:** Nodes send updates whenever ready. Better for dynamic networks.
- **Hierarchical FL:** Aggregation at multiple levels (sensor → gateway → cloud).

Hierarchical FL is most suitable for large scale sensor networks.

7. ENERGY EFFICIENCY CONSIDERATIONS

Training models consume energy. Methods to reduce energy:

- Model compression
- Quantization of weights
- Sparse updates
- Fewer communication rounds
- Duty cycling of sensors

Energy aware federated algorithms are required for embedded systems.

8. SECURITY AND PRIVACY ASPECTS

Though FL improves privacy, still some attacks possible:

- Model poisoning attack
- Data inference attack
- Eavesdropping during transmission

Solutions include:

- Secure aggregation
- Differential privacy
- Encryption of updates
- Trust management among nodes

9. CHALLENGES IN IMPLEMENTING FL ON SENSOR NODES

1. Memory limitation for ML models
2. Unreliable wireless connectivity
3. Non-IID data across sensors

4. Heterogeneous hardware
5. Limited battery life
6. Synchronization issues

These challenges makes direct implementation difficult and need optimized frameworks.

10. APPLICATIONS OF FL IN EMBEDDED SENSOR NETWORKS

10.1 Healthcare Monitoring

Wearable sensors collect ECG, heartbeat, temperature. FL allows training disease prediction models without sharing patient data.

10.2 Smart Agriculture

Soil moisture and climate sensors distributed over farms. FL helps to predict irrigation needs.

10.3 Industrial IoT

Vibration and temperature sensors for predictive maintenance. FL reduces data transfer to cloud.

10.4 Environmental Monitoring

Air quality and pollution sensors can collaboratively train prediction models.

10.5 Smart Homes

Motion and energy sensors learn user behavior locally.

11. ALGORITHMS USED IN FEDERATED LEARNING

- Federated Averaging (FedAvg)
- FedProx
- FedSGD
- FedMA
- Adaptive Federated Optimization

FedAvg is simple and widely used but not always efficient for non-IID sensor data.

12. HARDWARE PLATFORMS SUPPORTING FL

Some embedded platforms capable of running FL:

Platform	Features
Raspberry Pi	Enough RAM for small models

Platform	Features
ESP32	Low power, WiFi enabled
NVIDIA Jetson Nano	GPU for edge AI
ARM Cortex-M series	Ultra low power

TinyML frameworks also help to run ML on microcontrollers.

13. ROLE OF EDGE COMPUTING

Edge gateways play important role:

- Aggregation of models
- Temporary storage
- Pre-processing
- Security management

Edge computing reduces burden on cloud and sensors.

14. CASE STUDY: FL FOR AIR QUALITY MONITORING

Multiple air sensors placed across city. Each sensor trains local pollution prediction model. Gateway aggregates updates and forms global model. This model predicts pollution trend for entire city without sharing raw data from sensors.

Benefits observed: reduced bandwidth by 70%, improved privacy, faster predictions.

15. FUTURE RESEARCH DIRECTIONS

- Energy optimized FL protocols
- Lightweight ML models for microcontrollers
- Robust aggregation against attacks
- Handling non-IID sensor data
- Integration with 6G and LoRaWAN
- Self adaptive federated networks

16. CONCLUSION

Federated learning is very promising technique for embedded sensor networks where privacy, bandwidth and energy are main concerns. Instead of sending raw sensor data to cloud, local training and sharing model parameters gives efficient distributed intelligence. However many challenges like limited memory, energy, non-IID data and security issues still exists. With

advancements in TinyML, edge computing and communication technologies, federated learning will become key technology for future IoT and embedded applications.

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