FOTAS with Federated Learning: Redefining Acoustic Sensing for the Future

Bilgekul Kadirhan Karahan, Mustafa Bölükbaşı, İsmail Uzun,
Ramazan Can Şahin, Uğur Ataman

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1. Executive Summary

FOTAS is an advanced optoelectronic system powered by artificial intelligence, designed to measure and analyze acoustic parameters along the length of optical fiber. Built on the foundation of Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS) technologies, FOTAS delivers precise, real-time insights into physical environments over long distances—making it ideal for critical infrastructure monitoring, energy systems and security applications.

As data privacy, scalability, and real-time responsiveness become important in sensing systems, FOTAS is now enhanced with Federated Learning (FL) capabilities. This cutting-edge integration enables decentralized model training across multiple deployment sites—eliminating the need to transfer raw data to a central server. By doing so, FOTAS offers a privacy-preserving, bandwidth-efficient and scalable AI solution for distributed environments.

This white paper introduces the capabilities of FOTAS and explores how the integration of FL transforms it into a next-generation solution for industries that demand continuous monitoring without compromising data control. Readers from both business and academic domains will gain insight into how FOTAS addresses real-world challenges in sensing, while also pushing the boundaries of intelligent edge computing in optical fiber systems.

2. Problem Statement and Market Need

Modern sensing infrastructures—especially those deployed across extended physical environments—require high-resolution, real-time data to ensure reliability and efficiency. Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS) technologies have emerged as promising approaches for transforming conventional optical fibers into dense, high-frequency sensor arrays. However, as the volume, velocity, and variety of data increase, so do the computational and privacy challenges associated with centralized processing models.

Traditional machine learning techniques often rely on aggregating large-scale sensor data in central servers, which raises several concerns. First, transmitting raw data across networks can be inefficient and cost-prohibitive, particularly in bandwidth-constrained or remote environments. Second, centralized approaches create potential vulnerabilities in data security and system resilience. Finally, conventional models struggle to generalize across heterogeneous environments and infrastructure settings without significant retraining and manual calibration.

The need for distributed intelligence that is adaptive, privacy-preserving and collaborative has therefore become critical in both industrial and urban sensing applications. This is particularly relevant in domains such as smart infrastructure, rail transport, energy systems, and data center operations—each requiring context-aware, real-time analytics while maintaining strict control over data ownership.

To address these gaps, there is growing academic and industry interest in the application of **Federated Learning (FL)**—a decentralized machine learning paradigm that enables edge devices to collaboratively train models without transferring raw data. The integration of FL into optical fiber sensing systems like FOTAS presents a scalable and innovative approach to extending AI capabilities to the edge—enabling intelligent, distributed and privacy-conscious sensing across a wide range of operational environments.

3. Why Federated Learning?

Traditional AI systems in sensing technologies often rely on centralized data collection, which poses challenges related to privacy, bandwidth, and operational scalability, especially in distributed environments such as infrastructure monitoring or industrial facilities. Federated Learning (FL) offers an alternative by enabling AI models to be trained directly at the edge, where the data is generated. In the context of FOTAS, FL allows multiple sensing units to collaboratively learn from diverse acoustic and environmental conditions without sharing raw data. This not only safeguards sensitive operational information but also reduces data transmission loads and enables faster adaptation to local patterns. By embedding FL into FOTAS, the system evolves into a decentralized, intelligent sensing platform capable of supporting mission-critical operations in real time securely, efficiently, and with greater flexibility.

Comparison with Traditional Approaches

Feature / Approach	Traditional Centralized Sensing	FOTAS with Federated Learning
Data Management	Raw data transmitted to central server	Data stays local; only model updates shared
Bandwidth Usage	High, due to continuous data transfer	Low, only small model parameters transmitted
Privacy & Security	Higher risk of data exposure	Enhanced privacy; no raw data leaves the site
Scalability	Challenging with many distributed nodes	Highly scalable across multiple locations
Latency	Potential delay due to centralized processing	Real-time, localized processing and response
Context Adaptability	Models may not reflect local variations	Local training enables site-specific adaptation
System Resilience	Single point of failure risk	Decentralized architecture increases robustness

Table 1 - Comparison of the sensing approaches.

4. Introduction to FOTAS

FOTAS is an optoelectronic system enhanced with artificial intelligence, designed to measure acoustic parameters along the entire length of an optical fiber. It continuously generates and classifies acoustic profiles, providing critical data for data-driven analysis across various applications.

The device operates using a phase-sensitive OTDR (Optical Time-Domain Reflectometry) system. A laser injects light into the fiber optic cable, and due to the inherent structure of the fiber, a small portion of the light is scattered and reflected back to the source. This scattering effect allows the system to detect even the slightest disturbances or impacts on the cable with high precision.

One of the system's key advantages is its ability to work with standard industry-grade fiber optic cables without requiring any special cable type. Cables are installed along the area to be monitored, and an analyzer device can perform highly precise detection—up to 10-meter resolution over distances of up to 50 kilometers.

FOTAS (Fiber Optic-Based Acoustic Sensor) systems transform standard single-mode fiber optic cables into passive sensing networks, capable of detecting acoustic vibrations traveling underground or through surrounding media using the principle of Rayleigh scattering.

Figure 1 - Visualization of the FOTAS system in the field.

Physical Basis of Rayleigh Scattering

Rayleigh scattering arises from microscopic irregularities within the fiber core that scatter the injected laser light. This scattered light is highly sensitive to minute mechanical strains or deformations in the fiber caused by external acoustic or seismic activity. In DAS systems, a short-duration optical pulse (typically a few nanoseconds) is transmitted through the fiber. Backscattered signals are collected and analyzed using time-of-flight techniques to determine the spatial origin of the disturbance along the fiber.

FOTAS is highly sensitive to even the smallest movements in the fiber optic cable. Using advanced signal processing techniques, it effectively distinguishes relevant acoustic events from background environmental noise, significantly minimizing false alarms.

The system comprises three core components: the fiber optic cable running along the monitored path, a real-time signal analyzer, and a server that hosts intelligent signal processing and reporting software. For greater flexibility and ease of deployment, multiple analyzers can be connected to a single server.

Since FOTAS uses the fiber optic cable itself as the sensor, it detects motion via vibrations on the cable without requiring any external power supply along the cable route. Its passive sensing nature also makes it immune to electrical interference, lightning strikes, electromagnetic fields, and radio frequency signals. This ensures reliable and accurate performance in harsh and challenging environments while remaining a cost-effective solution for distributed physical sensing.

Differences at the Sensor Level

- Buried fibers are more effective at capturing direct ground motion, whereas surface-mounted fibers are more sensitive to acoustic resonances.
- Factors such as soil composition (e.g., soil, rock, concrete) and fiber construction (loose-tube, armored, etc.) affect the amplitude and propagation characteristics of the recorded signals.

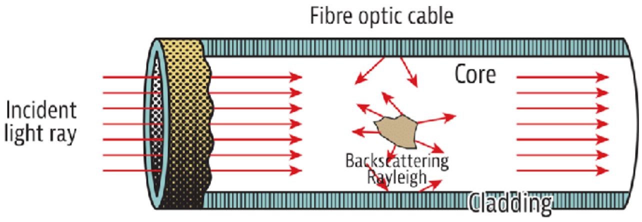

Figure 2 - Visualization of inside of the fibre optic cable.

Following Rayleigh scattering, the backscattered light from the laser is analyzed over 10-second time windows sampled at 2kHz. Within these temporal regions, the system assumes the possibility of acoustic activity and processes the signal accordingly.

The resulting signal vector, derived from distributed optical measurements, is binary encoded and interpreted as a 1-dimensional feature space. Using machine learning-based prediction algorithms, the system evaluates whether any acoustic event has occurred within the observed segment.

In this setup, the model specifically aims to detect the presence or absence of acoustic activity over a 10m section of the optical fiber. The trained algorithm classifies these segments in real-time, enabling intelligent monitoring and decision-making over large-scale distributed sensing networks.

Due to the high dimensionality and complex spatiotemporal patterns present in these raw signals, traditional signal processing techniques often fall short in achieving robust, real-time classification. To address this, we integrate a Convolutional Neural Network (CNN)-based deep learning framework that learns discriminative features from the raw signal directly and performs accurate detection and classification of acoustic events.

Each fiber segment (typically 10 meters) is sampled continuously at a rate of 2 kHz. Data is windowed into 10-second segments, yielding:

Input vector size = 10 sec × 2000 samples/sec = 20,000 time-domain samples

These 1D time-series vectors are used as direct inputs to the CNN architecture. Prior to model training, optional preprocessing such as normalization, wavelet denoising, or bandpass filtering can be applied to improve signal-to-noise ratio (SNR).

The CNN model is designed for 1D convolution, capturing local patterns and features across the temporal dimension of the acoustic signal.

The CNN model is integrated into the FOTAS data pipeline to operate in real-time. For each incoming 10-second signal window per 50m segment, the model performs:

- **Forward pass** to extract features and classify the segment
- **Segment-level decision making**, enabling geolocation of acoustic events
- **Low-latency alerting**, depending on application (e.g., intrusion, pipeline tapping)

This architecture is scalable, allowing parallel processing over hundreds or thousands of segments.

Two-Stage Predictive Architecture: Anomaly Detection and Event Classification

The signal interpretation pipeline in FOTAS is based on a two-stage deep learning architecture, designed to first detect whether any acoustic event has occurred, and then classify the type of event if detected. This modular approach improves both the reliability and interpretability of the system in real-world environments.

Stage 1: Anomaly Detection Model (Binary Classification)

The first model serves as a binary anomaly detector, which evaluates whether a given 10-second signal segment contains any acoustic anomaly or event-related activity. The input is a 1D time-series vector derived from Rayleigh backscattered signals. The output is binary:

- 0 – No event detected (background noise or static conditions)
- 1 – Anomalous signal detected (potential event present)

This model acts as a filter to eliminate unnecessary computation and false positives in the classification stage. In many deployment scenarios, over 90% of data segments contain no actionable events, making this first step critical for scalability.

Stage 2: Event Classification Model (Multiclass Prediction)

If an anomaly is detected, the signal segment is passed to a second model: a multiclass classifier, trained to identify the type of acoustic event. Example classes may include:

- 0 = walking
- 1 = climbing
- 2 = cutting
- 3 = vehicle movement
- 4 = manual & mechanical digging
- ... (expandable depending on use case)

This classifier is typically a deeper CNN or hybrid architecture (e.g., CNN + Transformer) capable of extracting more nuanced features specific to each event class.

The machine learning methods utilized in this project are primarily based on Convolutional Neural Network (CNN) architectures widely adopted in the literature. Throughout the project lifecycle, we have experimented with a range of advanced approaches, including mathematical feature engineering and alternative training paradigms such as transfer learning.

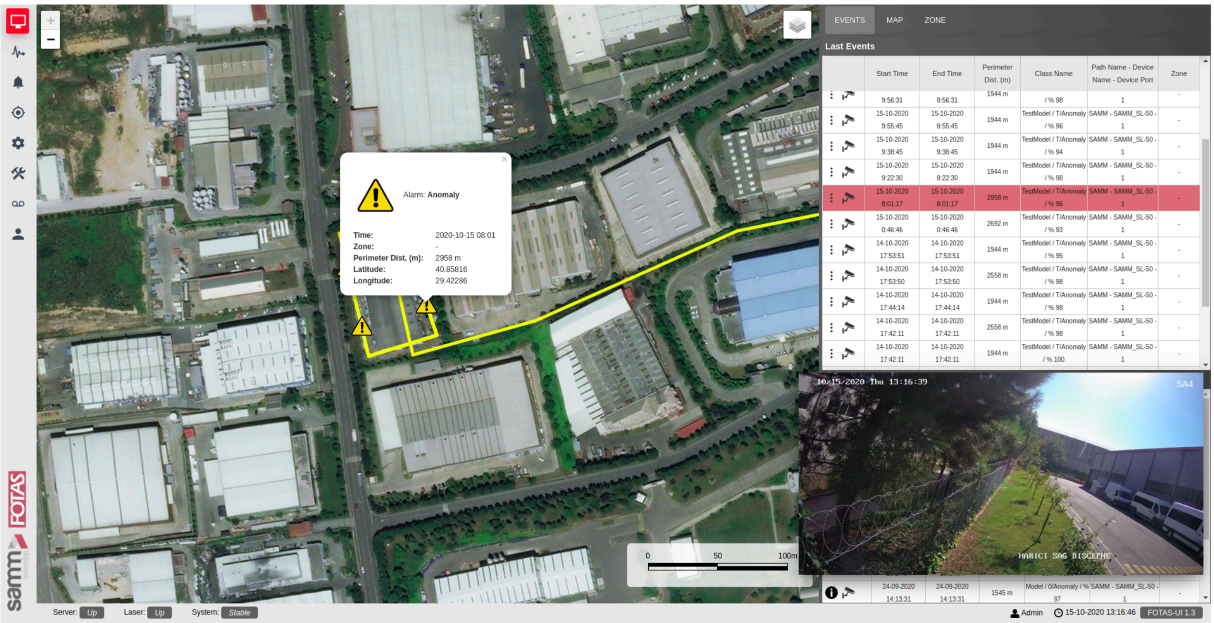

Figure 3 - FOTAS User Interface alarm scenario.

5. FOTAS-FL Platform System Architecture

The Fotas model is a Convolutional Neural Network (CNN)-based architecture designed to provide accurate binary or multiclass predictions from sensor data. Uniquely, the Fotas model operates directly on client servers, ensuring that sensitive raw data never leaves the local environment. Instead, model training is orchestrated through the Flaction platform, which serves as a centralized coordinator hosted on the main server.

Within this FL framework, each client server continuously collects data from its connected sensors. Once sufficient data is gathered locally, the training process is initiated on the client, and the model learns from its own private dataset. At the end of the training phase, only the model parameters (such as weights and biases) are securely transmitted to the main server—never the raw sensor data itself.

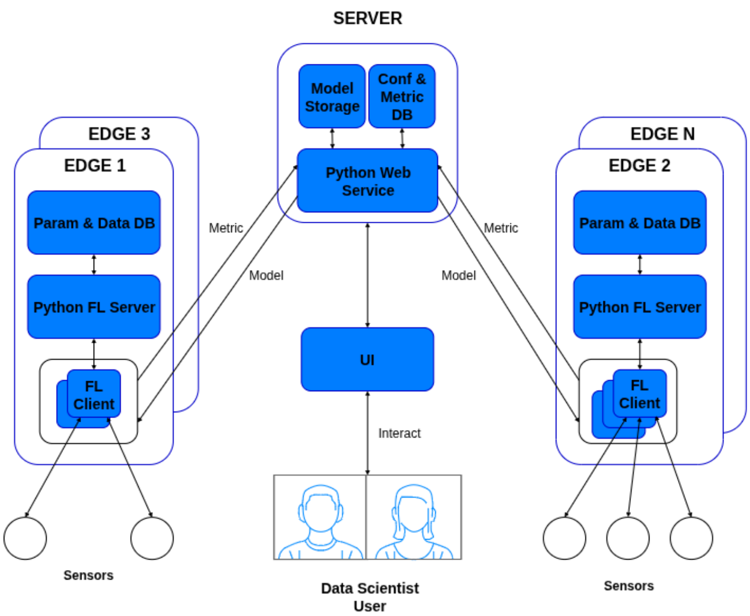

Figure 4 - Federated Learning Use Case Diagram

The main server aggregates these parameters, updates the global model, and redistributes the new model parameters back to all participating client machines. This decentralized approach enables all clients to benefit from the collective intelligence of the entire network, converging towards a shared model that reflects the diverse datasets distributed across the clients while strictly preserving data privacy and confidentiality. As a result, each client server operates with the latest model parameters, enabling robust and consistent performance across the platform, without any party accessing the original training data of another.

Furthermore, the FL platform is designed to be user-friendly for data scientists who may not have direct access to or knowledge of the underlying model architecture or datasets. Data scientists can easily manage critical aspects such as data collection rates, model update schedules and server/client configurations directly through the FL platform's interface. This abstraction allows them to focus on optimizing system performance and operational efficiency, without the need to handle sensitive data or detailed model internals.

6. Technical Insights

The platform leverages the Flower framework to implement FL within the system, ensuring scalable, flexible, and efficient model orchestration across multiple client devices. The core federated optimization algorithm utilized is FedAvg (Federated Averaging), which aggregates locally trained model parameters from participating clients to update the global model in a privacy-preserving manner.

A primary challenge in deploying the FOTAS system with FL capabilities arises from the availability and quality of data on client servers. Effective and robust model training relies heavily on sufficient labeled data distributed across clients. In scenarios where a client server does not possess enough labeled data, the platform is designed to automatically exclude that client from the current training round, thereby maintaining the overall training efficiency and integrity of the global model. The scarcity of labeled data remains a key risk in achieving optimal model performance and accurate predictions.

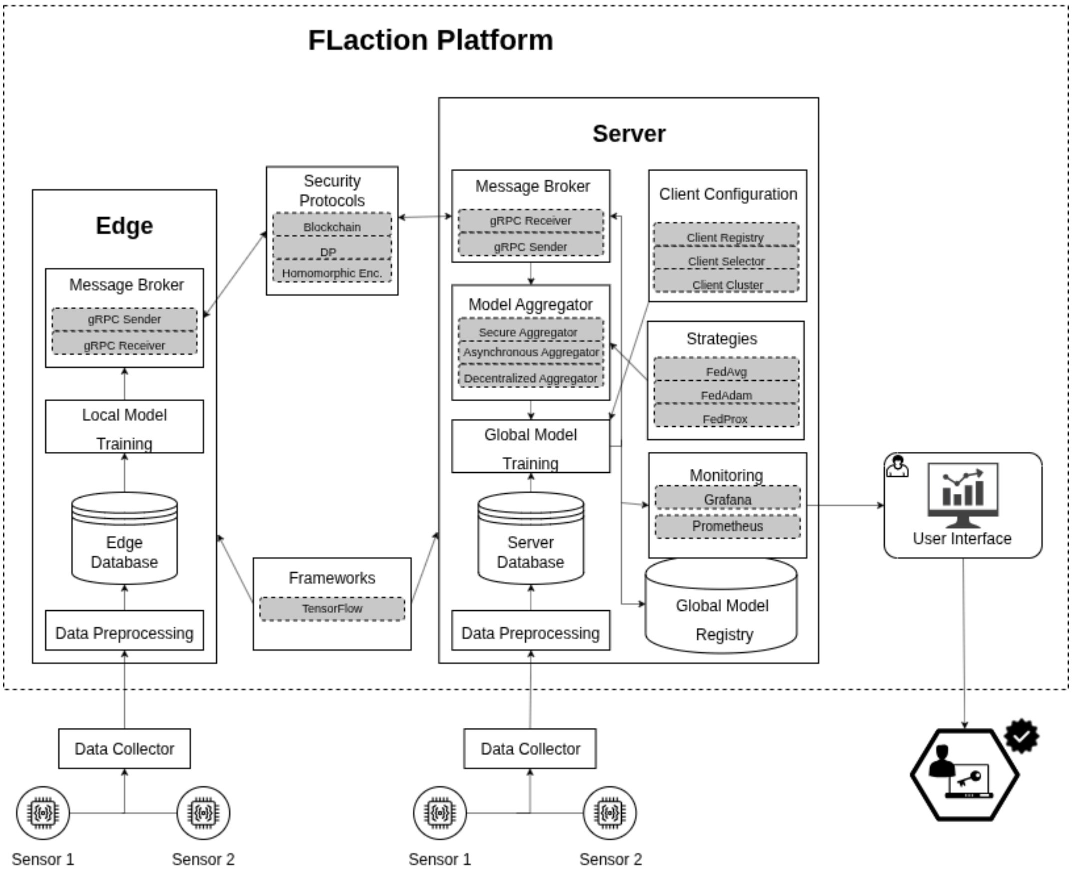

Figure 5 - FLAction System Architecture

To monitor and evaluate model performance during the training phase, the system tracks the validation loss (val_loss). For post-training assessment, key performance metrics such as recall and confusion matrix analysis are employed to measure test accuracy and identify potential misclassifications. Furthermore, to validate model performance in real-world operational settings, a waterfall testing approach will be applied, enabling comprehensive evaluation of model robustness and reliability in field conditions.

7. Use Cases and Benefits

By integrating Federated Learning (FL) into FOTAS, the system evolves beyond traditional sensing into a distributed, intelligent and privacy-preserving platform. This enables localized learning, real-time responsiveness, and secure collaboration across security-critical environments. Important use cases where FOTAS+FL delivers exceptional value are:

Facility Security

Facilities such as power plants, airports, data centers, and industrial complexes require continuous protection from intrusion, tampering, or sabotage. FOTAS detects and classifies acoustic anomalies—such as unauthorized movement, drilling, or breaking activities—along facility perimeters and infrastructure. With FL, each facility can train its own AI model based on its unique acoustic profile, layout, and operational noise patterns, without sending sensitive data off-site. This enables site-specific threat detection and higher accuracy with fewer false positives.

Border Security

Borders encompass vast and varied terrains, from deserts to forests and mountainous zones—each with its own acoustic characteristics. FOTAS can monitor for movement, tunneling, or ground disturbances across large sections of border infrastructure.

FL allows each border region to build localized models that understand region-specific acoustic signatures, environmental noise and threat patterns. This supports:

- Real-time situational awareness
- Low-bandwidth deployment over wide areas
- Secure collaboration between agencies without data sharing

Pipeline Security

Pipelines span thousands of kilometers through remote or inaccessible terrain and are exposed to risks such as illegal tapping, leakage and geotechnical stress. FOTAS enables early anomaly detection along the pipeline's entire length. With FL, models can be trained locally across pipeline segments by adapting to varying soil types, environmental conditions and operational noise and without transmitting raw acoustic data. Benefits include:

- Improved detection of leaks, tampering, or pressure anomalies
- Faster, location-specific response times
- Cost-effective and privacy-aware monitoring at scale

8. Conclusion

As sensing technologies evolve to meet the demands of complex, distributed, and security-critical environments, the combination of fiber-optic sensing with artificial intelligence marks a significant leap forward. FOTAS stands at the forefront of this transformation by delivering real-time, high-precision acoustic and temperature sensing along optical fibers for applications ranging from facility and border security to infrastructure monitoring and smart city development.

What sets FOTAS apart is its integration of FL which is a game-changing capability that enables decentralized model training directly at the edge.

FOTAS with FL is not just a sensor system—it's a future-ready platform that redefines how intelligent sensing is deployed, managed and secured.

9. References

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