

HackSky 2025

Round 1

Team Name: Overr1de

Team Members



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**This team has participated in the online evaluation round of the Manipal Hackathon
(Tech Tatva 2024)**

The Transformation of ICS and Cyber Threats

Motivation

- Industrial Control Systems (ICS) are the backbone of critical infrastructure—power grids, water treatment plants, and manufacturing lines.
- These systems face growing threats, such as sophisticated cyber-physical attacks and Limited visibility due to air-gapping, legacy devices, and lack of modern monitoring.

Challenge

How do we detect attacks without disrupting operations or installing intrusive sensors?

Introduction

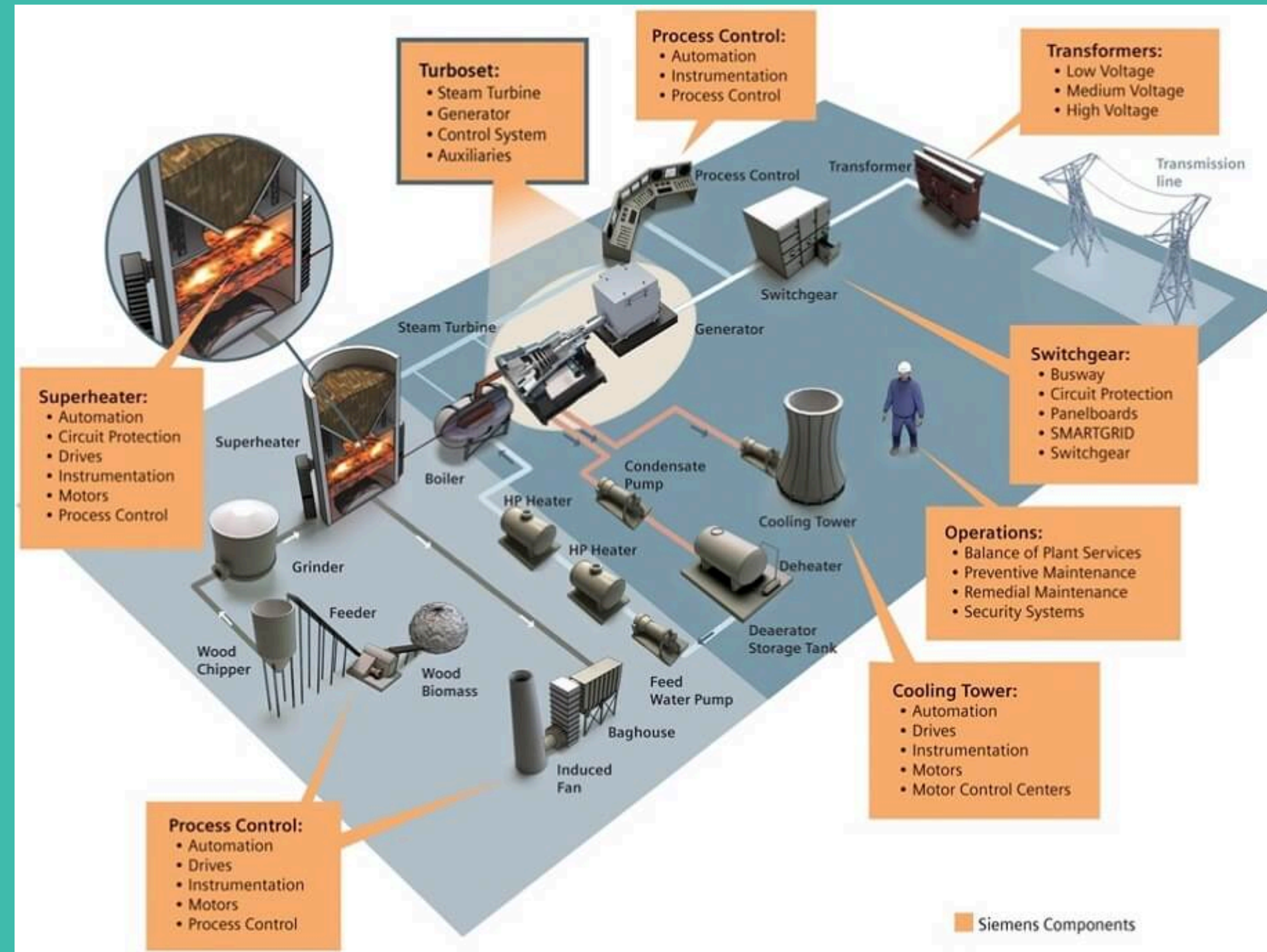


Fig. This illustration of a power plant shows the critical role of ICSs in energy infrastructure, where computer systems are situated in process control sections of the plant.

Our Idea

- Non-Intrusive Load Monitoring (NILM): Originally for smart homes, it can infer appliance-level behavior from total energy use.
- In ICS: Can we apply NILM-like techniques to detect malicious activity via indirect signals, without modifying existing infrastructure?
- Only access to the power supply via traces or a meter would be required to monitor multiple ICSs.

Train deep learning models on proxy data to detect anomalies and possible attacks

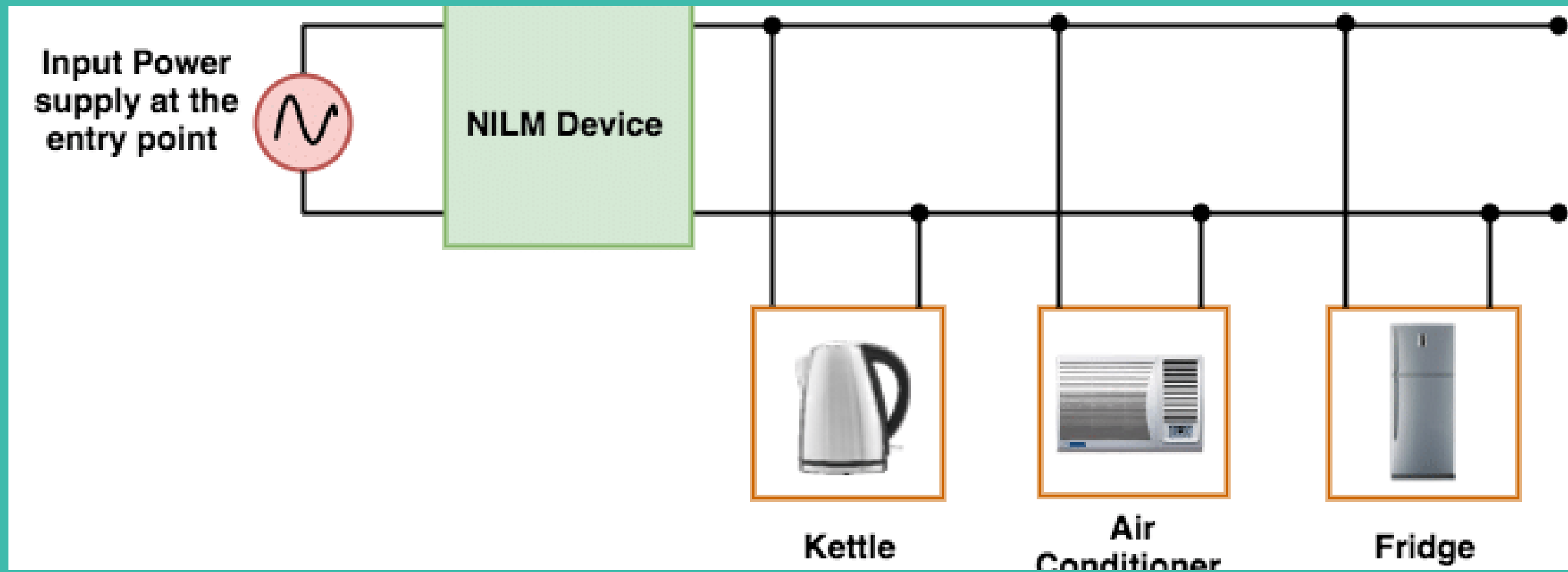


Fig: A typical NILM deployment in a home

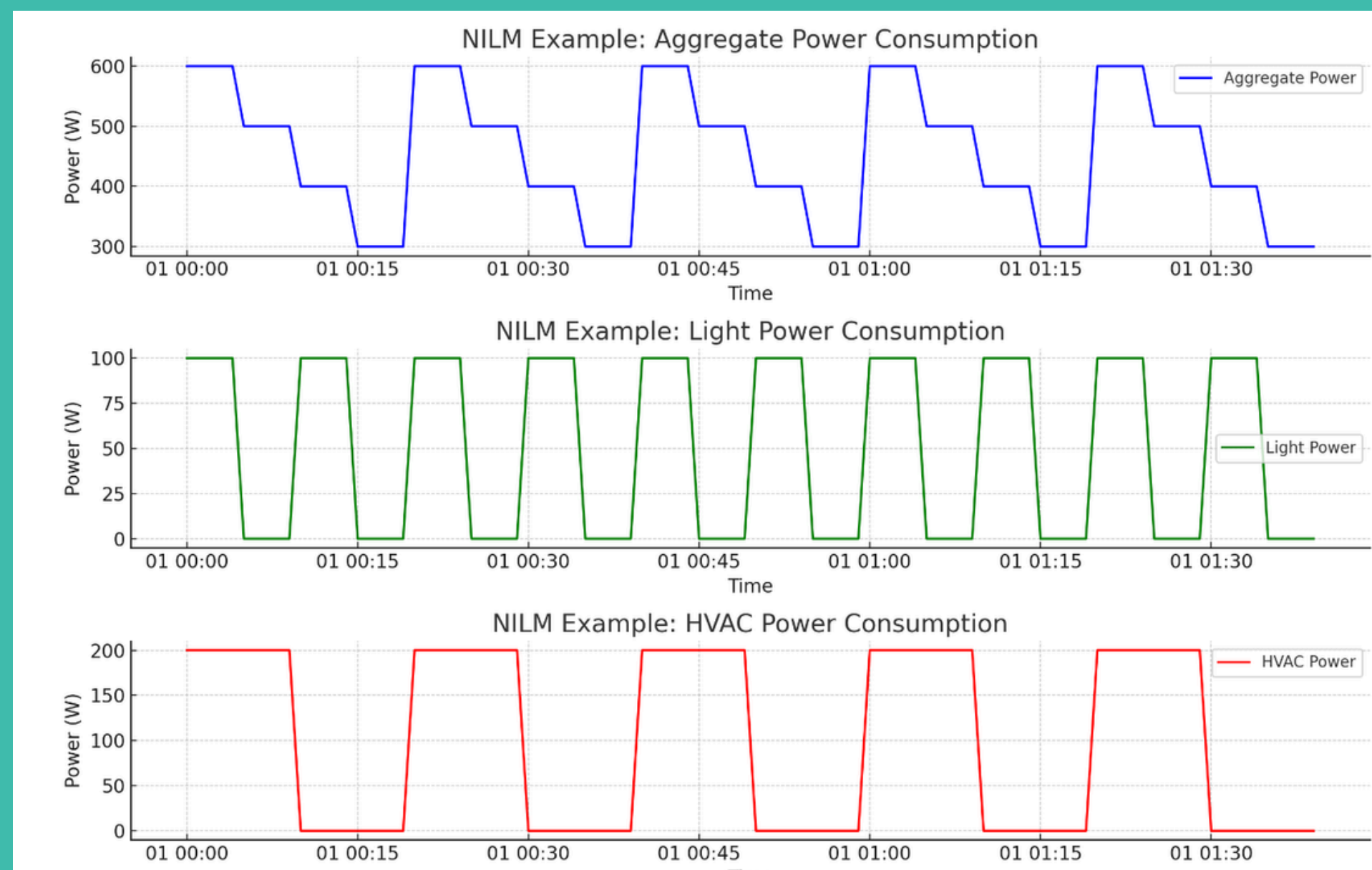


Fig: Time Series data showing NILM in action

Implementation

- Collect appliance-level power data from ICS environment (or simulated)
- Use it as a proxy to learn system behavior patterns
- Apply deep learning models, ie, 1D CNNs
- Train on normal & attack scenarios (or unsupervised for anomaly detection)
- Output: detect deviations and flag as potential cyber-physical attacks

Plan

- Simulated ICS + appliance-level power traces
- Preprocessing
- Normalize, window, label proxy signals
- Model Development and decide on architecture
- Train deep learning models (1D CNN or LSTM)
- Evaluation of models
- Test in a closed-loop ICS environment

Challenges

- Proxy Gap: Appliance behavior may not always reflect internal ICS state
- Data Scarcity: Real ICS attack datasets are rare or classified, and using proxy data could pose a formidable challenge
- Noise & Variability: Electrical signals are noisy & environment-dependent
- Generalization: Models trained on one setup may not transfer easily
- Explainability: Black-box DL models makes it hard to interpret for operators

Data Simulation & Preprocessing

- Python, NumPy, Pandas, SciPy
- Optionally: OpenDSS, GridLAB-D (for ICS load sim)

Deep Learning Models

- PyTorch
- Scikit-learn for ML baseline
- TorchTS / PyTorch Forecasting for time seires

Visualization & Evaluation

- Matplotlib, Seaborn
- TensorBoard / Weights & Biases (optional)

Deployment/Prototyping

- Jupyter for experiments
- Docker (if containerizing)
- Raspberry Pi / low-power edge device (future deployment)

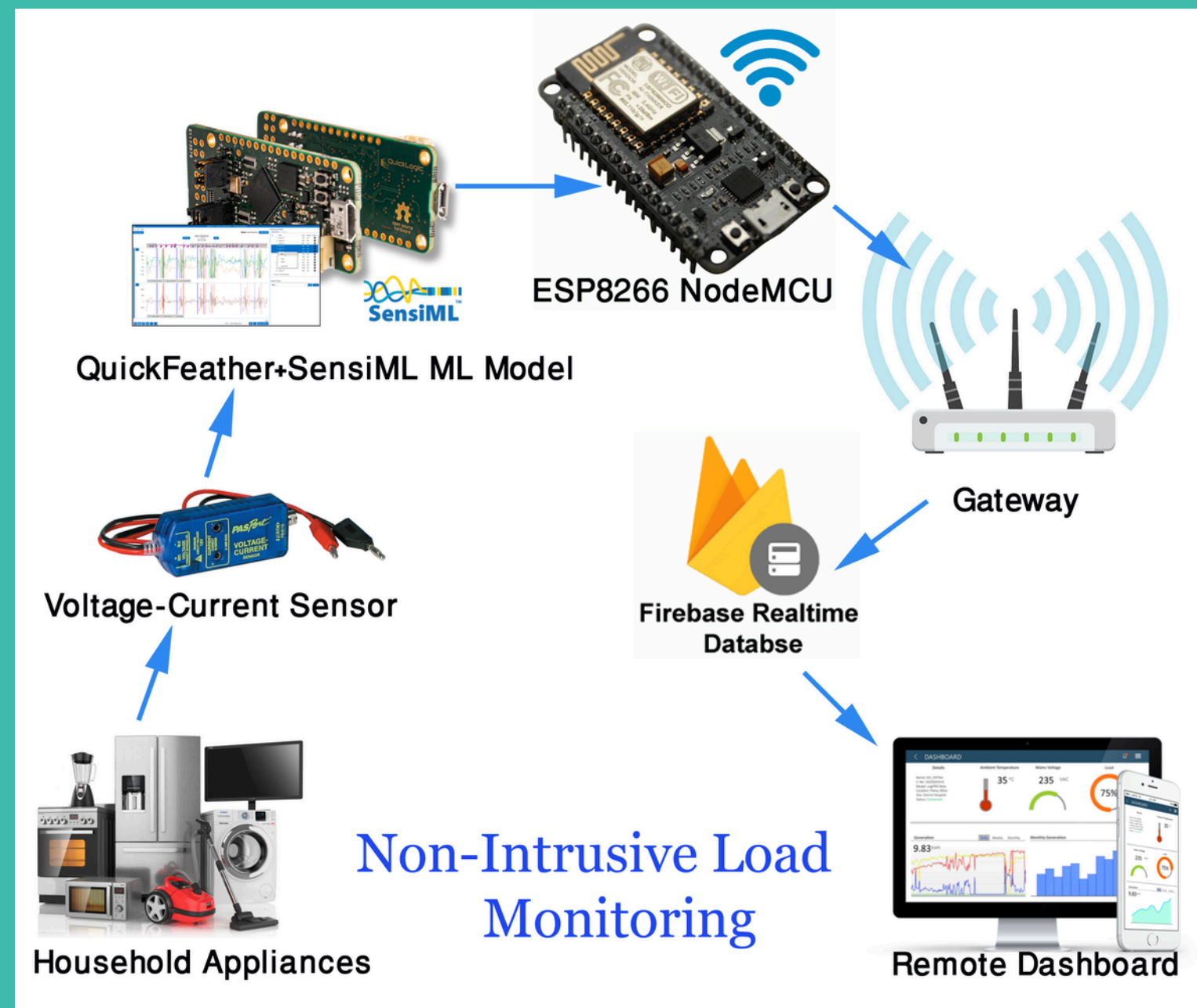


Fig: An ideal NILM deployment with an edge device. For our use case, we would monitor ICSs instead of appliances.

Multi-modal Proxy Signals

- Combine power data with other signals (e.g., EM emissions, timing patterns, network activity)

Real-world ICS Integration

- Deploy in real ICS testbeds with live industrial workloads

Self-supervised & Continual Learning

- Adapt models to new devices and unseen attack patterns over time

Edge Deployment

- Run lightweight models on embedded devices for on-site anomaly detection

Explainability & Operator Trust

- Add interpretability tools using xAI to help ICS operators understand alerts