PhD Topic

FLEX-E: Explainable Hybrid Federated Learning for Energy Optimization in Industrial Parks

Keywords: Federated Learning, Industrial Energy Optimization, Explainable Artificial Intelligence (XAI), Physics-Informed Machine Learning, Knowledge Graphs.

Context

Industrial parks are major contributors to global energy consumption and CO_2 emissions due to their high demand, heterogeneous energy users, and complex energy flows [2, 8]. Improving energy efficiency in these environments is therefore a key lever for achieving climate targets, reducing operational costs, and strengthening regional competitiveness, particularly in industrially dense regions such as the Upper Rhine area. Despite their importance, conventional energy management systems are typically designed as isolated solutions. They lack the capability to address large-scale challenges such as decentralized energy optimization, integration of renewable energy sources (e.g. photovoltaic systems, waste heat recovery), and coordinated load balancing across multiple stakeholders. While collaborative energy platforms offer significant potential, their real-world deployment is constrained by strict requirements regarding data security and privacy, scalability, and adaptability to changing industrial infrastructures.

The FLEX-E project[1] addresses these challenges by introducing a collaborative energy optimization framework based on Federated Learning (FL). FL is a decentralized machine learning paradigm in which local entities—such as buildings, energy producers, or consumers—train models locally and share only abstracted model parameters rather than raw data. This approach enables cross-organizational learning while preserving data sovereignty, ensuring privacy, and supporting scalable deployment. In FLEX-E, this federated approach is combined with energy flow modeling based on digital twins and validation in real and planned industrial park testbeds of varying sizes. The project thus provides a unique foundation for advanced research into secure, data-driven, and collaborative energy management systems for industrial environments.

Proposed methodology and objectives of these PhD works

The increasing electrification of industry, coupled with the integration of renewable energy sources and flexible loads, has significantly increased the complexity of energy management in industrial parks. Figure 1 shows the setup of these systems. These environments are characterized by heterogeneous assets, distributed ownership, and strict requirements regarding data privacy and operational confidentiality. Traditional centralized energy management systems struggle to scale under these constraints and often fail to fully exploit collaborative optimization potentials.

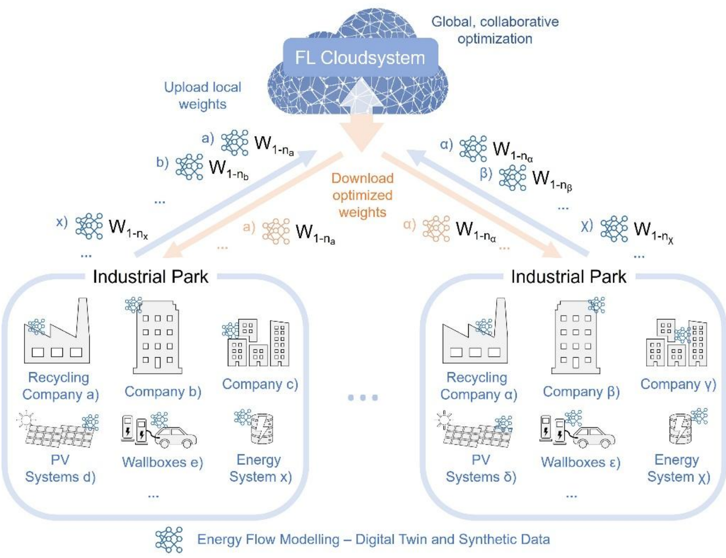

Figure 1: A federated learning framework integrating heterogeneous participants across industrial parks.

[1] https://www.interreg-rhin-sup.eu/projet/flex-e/

Recent advances in Federated Learning (FL) provide a promising alternative to centralized energy management approaches. Originally introduced to enable privacy-preserving machine learning across distributed data sources [5, 9], FL allows models to be trained locally while sharing only model updates instead of raw data. In the energy domain, FL has been explored for applications such as load forecasting, demand response, and smart grid optimization, demonstrating improved privacy preservation and scalability compared to centralized approaches [6, 10, 4]. However, most existing works focus on residential or grid-level scenarios and rely predominantly on data-driven models, offering limited interpretability and weak integration of physical and expert knowledge. These limitations are particularly critical in industrial environments.

This PhD project aims to advance the state of the art by developing an explainable and hybrid federated learning framework for energy optimization in industrial parks, building upon the FLEX-E project. The proposed approach combines data-driven federated learning with expert knowledge, including physics-based energy models, digital twins and knowledge graphs, to improve robustness, generalization, and trustworthiness of AI-based energy management systems.

More specifically, a first core research question (**RQ1**) investigates how federated learning architectures can be designed to optimize energy flows in heterogeneous and decentralized industrial parks while preserving data privacy and confidentiality [5]. To address this, the project will develop federated learning models trained locally on heterogeneous energy data originating from buildings, industrial processes, photovoltaic systems, energy storage units, and electric mobility infrastructure. At the global level, aggregation strategies will be adapted to the specific characteristics of industrial energy systems, explicitly addressing non-identically distributed (non-IID) data across decentralized industrial energy systems, varying operational constraints, and different scales of industrial parks.

To overcome the limitations of purely data-driven federated learning, the PhD will further address a second research question (**RQ2**): how physics-based energy models and physical constraints can be integrated into federated learning to improve robustness, generalization, and physical plausibility [7]. Physics-informed learning strategies will be embedded into model architectures and loss functions, incorporating constraints such as energy balance equations, capacity limits, and thermodynamic principles. Digital twins will be used to support model validation, scenario analysis, and learning under sparse or evolving data conditions.

In parallel, the project will investigate a third research question (**RQ3**): how knowledge graphs representing industrial energy systems can be combined with federated learning to enable context-aware aggregation, semantic understanding, and explainability. Knowledge graphs [3] will encode expert knowledge about industrial assets and energy flows, enabling federated models to exploit semantic context during training and aggregation. By linking model outputs to interpretable entities and relationships, these representations will provide a foundation for transparent and actionable insights.

A particular emphasis of the PhD will be placed on explainable federated learning [1]. Explainability methods compatible with privacy-preserving constraints will be investigated by combining local explanation techniques with reasoning over knowledge graphs and digital twins. This integrated approach aims to address a critical gap in current FL-based energy management research, where model decisions often remain opaque to system operators and industrial stakeholders.

Based on these research questions, the main objectives of the PhD can be summarized as follows:

- To develop a privacy-preserving federated learning framework tailored to industrial energy management.
- To integrate physics-informed modeling and expert constraints using knowledge graphs into federated learning workflows for improved interpretability and reasoning.
- To deliver explainable and trustworthy AI solutions for industrial energy optimization.

The proposed methods will be validated in real and simulated industrial parks of different sizes, with a focus on quantifying improvements in energy efficiency, CO_2 emission reduction, scalability, and user acceptance. The results are expected to support the transfer of the developed solutions to other industrial parks, including cross-border and multi-regional contexts, and to contribute to the development of trustworthy, privacy-preserving AI for industrial energy systems.

Environment

The PhD is fully funded for 3 years (part of the Interreg-funded FLEX-E project) and will start in Spring 2026. The PhD student will be welcomed in the SDC (Science des Données et Connaissance) team of the ICube laboratory at INSA Strasbourg, and supervised by Associate Professor Ahmed Samet, Associate Professor Franco Giustozzi and Associate Professor Edouard Walther.

Candidate

We are looking for a highly motivated PhD candidate with a Master (or engineer) degree (Bac+5 level) with a strong background in computer science or data science or energy systems, or a closely related field. Experience with Python and common ML frameworks (e.g. PyTorch, TensorFlow) is expected. A background or demonstrated interest in energy systems, smart grids, or industrial energy management is highly desirable. Familiarity with physical modeling, optimization, or digital twins is an advantage. Interest in explainable AI, hybrid modeling, or knowledge graphs is a plus.

How to apply

The interested candidates must send an email to Franco Giustozzi (franco.giustozzi@insa-strasbourg.fr), Edoaurd Walther (edouard.walther@insa-strasbourg.fr) and Ahmed Samet (ahmed.samet@insa-strasbourg.fr) with the following documents:

- A CV,
- A cover letter (max. 1 page), including the applicant's motivation for applying and a brief explanation of their academic background,
- A transcript of the available grades for the current year and the past year,
- Recommenation letters or contact information of at least two referees.

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