CIFRE PhD position 2025

Foundation Models for Spatio-Temporal Aggregation of Weather Forecasts

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Location: EDF Lab Paris-Saclay, Département SEQUOIA, Groupe SOAD (Statistique et Outils d'Aide à la Décision), 7 boulevard Gaspard Monge, 91120 Palaiseau.

Academic Lab: Sorbonne Université, Campus Pierre et Marie Curie

Candidate profile: Master's degree or Engineering school. Background and experience in Machine Learning/Deep Learning. Good technical skills in programming with python.

Starting date: Q4 2025 for three years.

How to apply: Please send a CV, motivation letter, grades obtained in master, recommendation letters when possible, to the contacts.

Keywords: weather forecast, deep learning, aggregation, foundation models, renewables forecasting

Context

Électricité de France (EDF) is one of the world's leading electricity producers and suppliers, with a strong presence in nuclear, hydraulic, and renewable energy generation. To optimize energy production, ensure grid stability, and anticipate electricity consumption, EDF relies heavily on accurate and rapid weather forecasts. Weather variability directly affects renewable energy sources such as wind and solar power while also influencing electricity demand, particularly during extreme weather events. As a result, high-quality weather forecasting models are essential for EDF's operational efficiency.

Historically, weather forecasting has been based on **Numerical Weather Prediction (NWP) models**—physics-based models developed by leading meteorological institutions such as Météo-France and the European Centre for Medium-Range Weather Forecasts (ECMWF). These models numerically solve partial differential equations governing fluid dynamics and thermodynamics to simulate atmospheric behavior. However, running NWP models is computationally expensive and time-consuming. Their spatial and temporal resolutions remain limited, restricting their ability to provide highly localized forecasts. For example, ECMWF's most accurate global model currently operates at a 9 km spatial resolution with hourly updates.

In recent years, a new generation of **data-driven weather models** has emerged, including PanguWeather (Huawei), Aurora (Microsoft), FourCastNet (Nvidia & LBNL), GraphCast (Google), and AIFS (ECMWF). Unlike NWP models, these Deep Learning models rely solely on vast amounts of historical meteorological data, without explicit physical parameterization. They can generate global weather forecasts up to seven days ahead in just seconds on a single GPU (Pathak et al., 2022, p.16), achieving forecast accuracy comparable to traditional NWP while drastically reducing computational costs—orders of magnitude lower than the O(1000) CPUs typically required for NWP simulations.

However, despite these significant advancements, two major challenges remain:

1. Model performance varies depending on location and time of day. The best-performing model for a given region or time frame is not necessarily the most accurate elsewhere.

2. Data-driven models still struggle to represent local phenomena at high resolution, as demonstrated in the recent study by Schultz et al. (2021).

Whether based on traditional NWP methods or modern AI-driven approaches, current weather models **lack the necessary granularity** required for EDF's operations. EDF's activities demand **high-resolution, localized forecasts** that account for heterogeneous variables across multiple spatial and temporal scales. Therefore, it is essential to **adapt and refine existing weather forecasting models** to meet EDF's specific needs. A key challenge is determining how to **leverage the complementarity of physics-based and data-driven models** to enhance forecast accuracy by combining their strengths.

To achieve this, several research challenges must be addressed, including:

- **Hybrid modeling:** Combining different modeling approaches—whether physical or deep learning-based—to improve forecast accuracy.
- **Downscaling techniques:** Improving the resolution of weather forecasts at local scales.
- **Uncertainty modeling:** Developing robust approaches to quantify and reduce forecast uncertainty.

Objectives and industrial challenges

Development of a DL model for spatio-temporal aggregation of weather forecasts from different sources/types:

- capable of adapting - interpolation/extrapolation - to different geographical scales: national/local/power plant
- capable of exploiting spatio-temporal statistical relationships between grid points and at different resolutions
- whose forecasts are fed into renewable energy production and electricity consumption forecasting models to improve their predictive performance.

Research directions

Literature review:

Literature review on DL models for weather forecasting and comparison with NWP models
Catalog the characteristics of AI weather models: spatial and temporal resolution, reanalysis data used, update frequency, etc.
Identification of their strengths and weaknesses

Data reconciliation:

Combining grids from different spatial and/or temporal resolutions
Spatio-temporal relationships/correlations calculation and learning
Optimizing computation times

Development of Deep Learning models for spatio-temporal aggregation:

Proposition of a representation space for spatio-temporal data (value, position, time step)
Grid points selection method
Mixture model for these data/representations

Application for renewable energy forecasting:

Feed EDF's operational R38 model and evaluating performance.
Feed and optimize ML models for weather forecasts conversion into renewables production forecasts.

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