Foundation Model for Graph Structured Time Series Forecasting

1 Objective

The accurate prediction of power generation within an electricity system is essential for ensuring grid stability and optimizing energy utilization. However, the inherently stochastic nature of wind power, influenced by various factors such as meteorological conditions and geographical characteristics, presents considerable challenges for precise forecasting of short- and long-term power generation. Additionally, it complicates tasks related to fluctuation type classification, anomaly detection, and imputation of missing values.

In our preceding investigation, we introduce a systematic taxonomy that categorizes existing time series forecasting(TSF) methods into four distinct classes: traditional approaches, Fourier convolution-based methods, transformer-based models, and spatial convolutional-based techniques, along with foundational models. Our primary scientific objective is to augment the effectiveness of the aforementioned downstream tasks concerning power grid frequency datasets, while simultaneously ensuring computational efficiency, interpretability, and scalability.

Through this initial exploration, our overarching aim is to establish benchmarks for current methodologies and derive valuable insights to guide future research endeavors.

2 Approach

In our exploration, we intend to conduct a comparative evaluation of three distinct pipelines: traditional methodologies, Fourier convolution-based methods (FConvNets), transformer-based models, and a novel addition of large language model-based approaches (LLM). FConvNets, emerging as a promising paradigm this year, endeavor to implement nonlinear operations in the frequency domain. This framework has demonstrated superior accuracy coupled with reduced complexity, attributed to a narrower range of dynamic values. Conversely, LLM, transposing the principles of natural language processing, endeavors to predict the subsequent token within a time series context. Trained across a corpus of 42 datasets, LLM endeavors to establish a robust and adaptable prior for time series forecasting. Through this pilot project, we aim to furnish insights into the relative efficacy and prospective advancements within the realm of energy forecasting.

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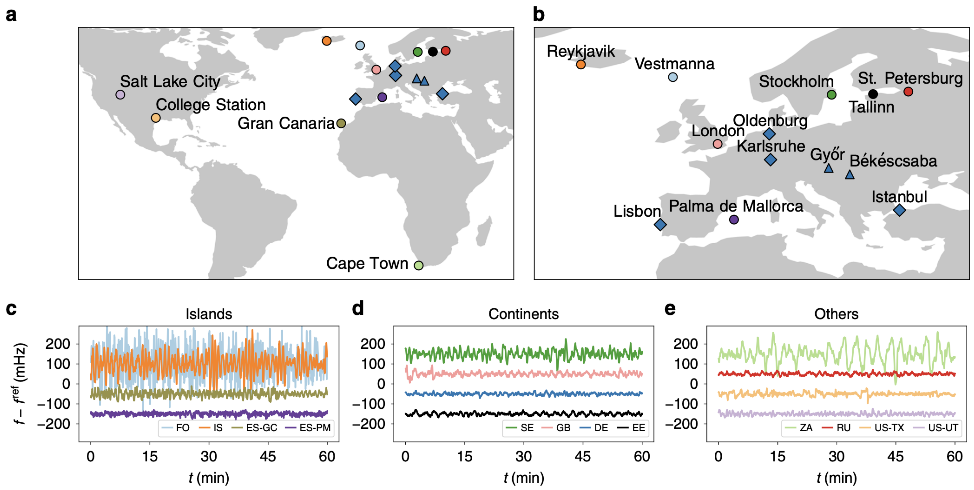

Fig. 1 Overview of available frequency data. a Different locations in Europe, Africa, and Northern America at which frequency measurements were taken. Australia and large parts of Asia are not displayed, as there were no measurements recorded. **b** Zoom of the European region (excluding Gran Canaria) with all locations labelled. Circles indicate measurement sites where single measurements for several days were taken, diamonds mark the four locations where we performed GPS-synchronised measurements, and triangles mark sites for which we received additional data. **c–e** Frequency trajectories display very different characteristics. We plot 1 h extracts of the deviations from the reference frequency of $f^{\mathrm{ref}} = 50$ Hz (or 60 Hz for the US power grids), which are offset from the zero mean to improve readability. Panels **c–e** and following plots abbreviate the measurement sites using the ISO 3166 code for each country and each location is assigned a colour code, as in the maps in **a** and **b**. For more details on the data acquisition and measurement locations, see Supplementary Note 1 and ref. [32]. Maps were created using Python 3 and geoplots.

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