DEVELOPMENT OF A MACHINE-LEARNING-BASED UP-SAMPLE ALGORITHM FOR WIND TURBINE TIME SERIES

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Content

The power system of the future faces a number of demanding challenges, which includes the increasing integration of renewable energies, particularly from wind power and solar radiation. In order to analyse the impact on the power grid, high-quality time series of power generation from wind turbines and photovoltaic systems are essential for given power system simulation. Renewable energy time series can be created based on historical measurement data from meteorological weather stations, such as the ERA5 dataset, but are limited to low temporal resolution, such as hourly data [1].

This work addresses this gap by introducing a machine-learning-based up-sampling algorithm that increases the temporal resolution of a given wind turbine time series from hourly values to minute-level values. While there are many contributions to wind speed prediction using machine learning, there is little literature on machine-learning-based up-sampling methods for such time series data [2]. A literature review was conducted, examining existing approaches for up-sampling of wind turbine time series. Based on the given findings, an innovative machine learning algorithm is introduced for executing the given up-sampling task. To carry out this study, an open-source dataset containing minute-level measurements from a wind farm with seven wind turbines was used. This dataset is comprehensive, including features such as power generation, wind speed and blade pitch angle [3]. Finally, results are presented, discussing the capabilities and limitations of the given approach.

Methodology

Before the actual model training, a preprocessing step is applied to the measurement data, to improve the model's performance. The simplified process is illustrated in Figure 1. Firstly, the signal is decomposed into a low-frequency baseline trend (C_t) via cubic spline interpolation and a high-frequency fluctuation signal (X_t) by subtracting the trend from the minute-level data. Therefore, the model is trained solely on the fluctuation of the signal, since the general trend is already known from the low-resolution data. Second the Fast Fourier Transform (FFT) is applied to the fluctuation signal, transforming the time series into magnitude, phase coefficients, which serve as prediction targets for the model. These coefficients represent the different fluctuation components and are used for model training.

Furthermore, a Long Short-Term Memory (LSTM) model was implemented, due to its capability of performing sequence learning tasks. This results in an up-sampling model, capable of increasing the temporal resolution of wind turbine timeseries, by introducing volatility patterns into the signal, which are not visible with low resolution data.

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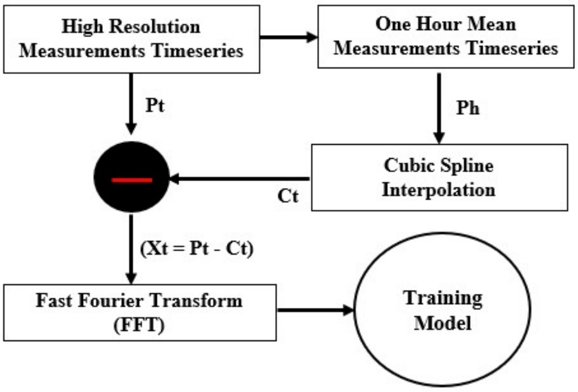

Figure 1 Training Step for Long Short-Term Memory – Frequency Based Model

The reconstruction process involves applying the Inverse Fast Fourier Transform to the predicted coefficients, resulting in the predicted fluctuation signal (Xt) which is then added back to the reference curve (Ct) to yield the final high-resolution output (Pt) (cf. Figure 2).

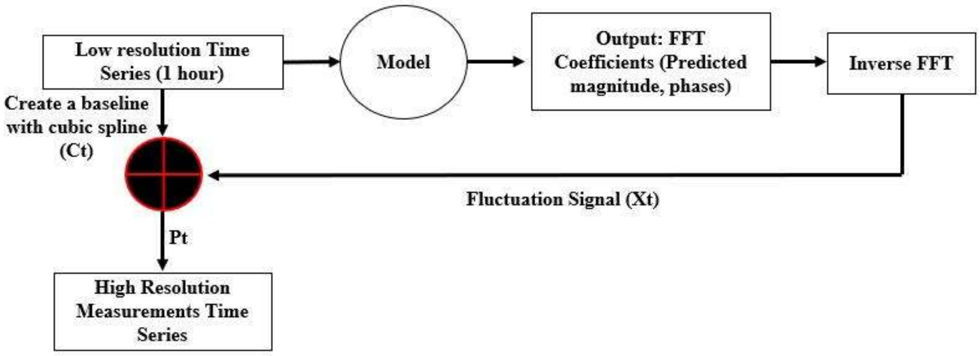

Figure 2 Application for Long Short-Term Memory - Frequency Based Model

Results

The results indicate the capability of the proposed model to increase the temporal resolution of wind turbine time series, by combining a Fast Fourier Transform with a Long Short-Term Memory model, based on publicly available wind turbine data. The evaluation metrics utilized include the Coefficient of Determination to assess the overall goodness of fit and general trend reconstruction, and the Volatility Similarity Score, which is crucial for quantifying the model's success in capturing sudden, high-frequency fluctuations. The findings demonstrate that the proposed Frequency Based LSTM model exhibits superior performance compared to both traditional interpolation methods and time-domain approaches.

References

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