A hybrid solution for wind resource assessment - predict offshore wind from limited onshore measurements

Basem Elshafei, Xuerui Mao
University of Nottingham

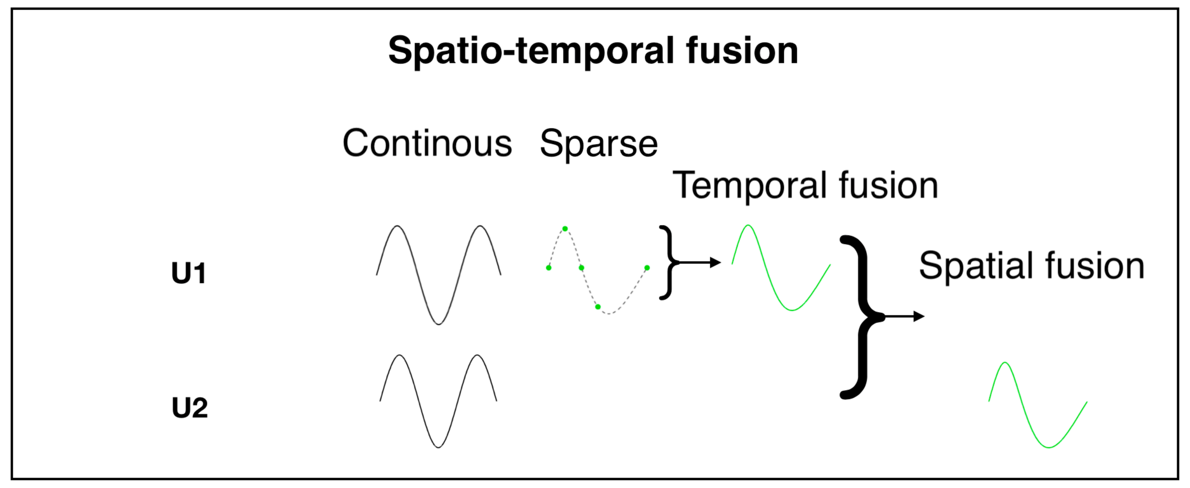
Jake Badger, Alfredo Pena
Technical University of Denmark

Abstract

In wind resource assessments, which are critical to the pre-construction of wind farms, measurements by lidar are a source of high-fidelity data, but are expensive and scarce, particularly for offshore sites. On the other hand, numerical simulations using, mesoscale models, for example the Weather Research and Forecasting (WRF) Model, generate temporally and spatially continuous data with relatively low-fidelity. A hybrid approach is proposed here to combine the merit of measurements and simulations for the assessment of offshore wind. Firstly a temporal data fusion using deep multi-fidelity Gaussian process regression is performed to combine the intermittent and short measurement and the continuous and long simulation data at an onshore location Then a spatial data fusion using neural network with non-linear autoregression (NAR) and non-linear autoregression with external input (NARX) are conducted to project the data from onshore to offshore.

Framework of Study

- Assessments of wind speed are critical to the pre-construction of wind-farms.
- High-fidelity measurements of wind speed can be obtained by lidars but are expensive and scarce.
- Continuous data can be generated using, numerical simulations' mesoscale models , with relatively low-fidelity.
- A hybrid approach is proposed to combine the merit of measurements and simulations for the assessment of offshore wind.



Flow chart for spatiotemporal fusion.
U1 and U2 represent the wind speed at two positions. They correspond to onshore and offshore wind, respectively.

Methodology

Temporal Fusion:

- **Multi-fidelity Gaussian Process Regression:**

Considering the high-fidelity data, $\mathbf{F_h}$, is a function of time **t** and the low fidelity data $\mathbf{F_L}$.

$$F_h(t) = g\ (t, F_l(t)), \qquad g(t, s) \sim \mathrm{GP}(\mathrm{m, k})$$

m is the mean function, and *k* is the covariance matrix function.

- **Nonlinear auto-regressive Gaussian Process** (further considering the derivations of the low fidelity data)**:**

$$F_h(t) = g\ (t, F_l(t), F^1{}_l(t), F^2{}_l(t), F^3{}_l(t), \ldots)$$

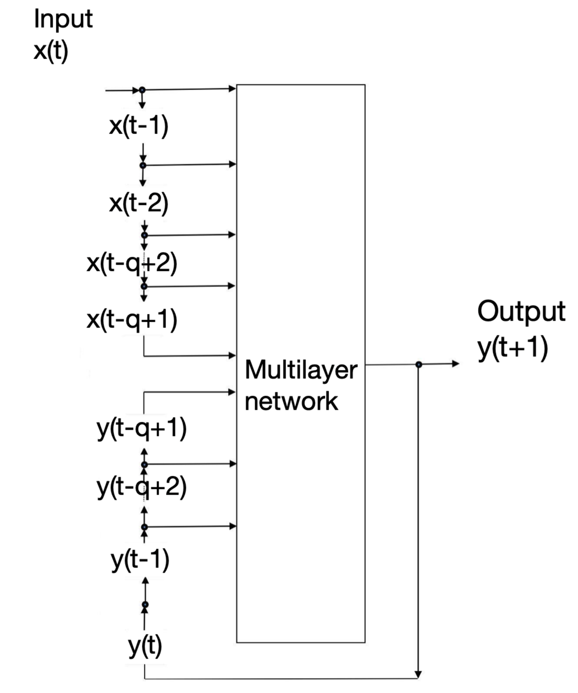
Spatial Fusion:

- **Nonlinear auto-regression with external input (NARX):**

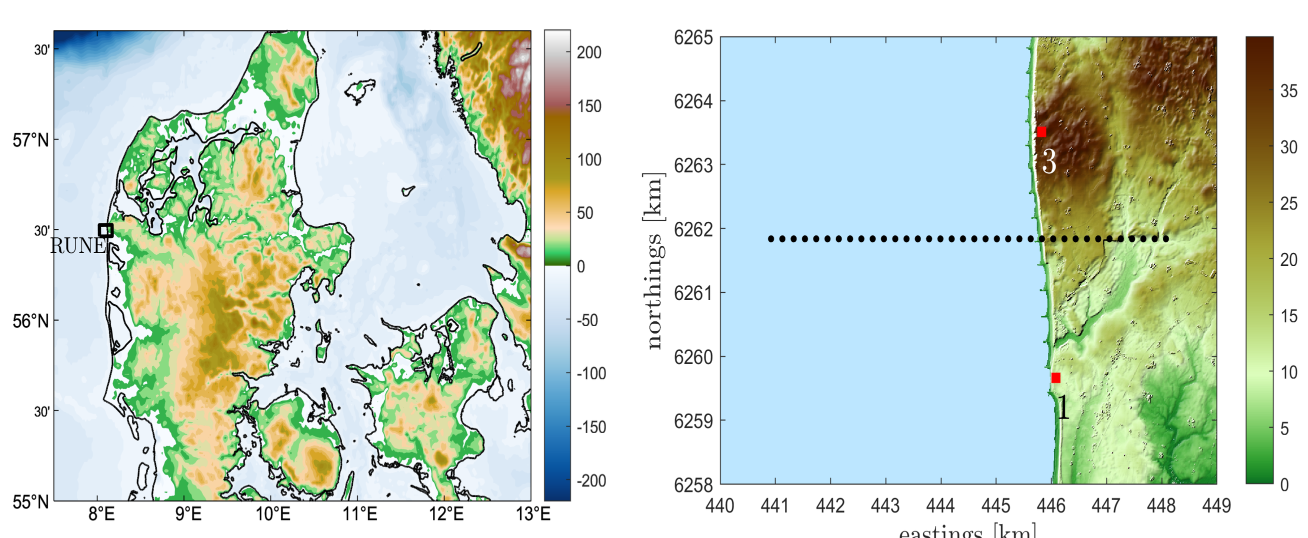
predicts $y(t)$ from its history and additional input $x(t)$:

$$y(n+1)=F[y(n), y(n-q+1), u(n), u(n-q+1)]$$

Framework for NARX model



Case description

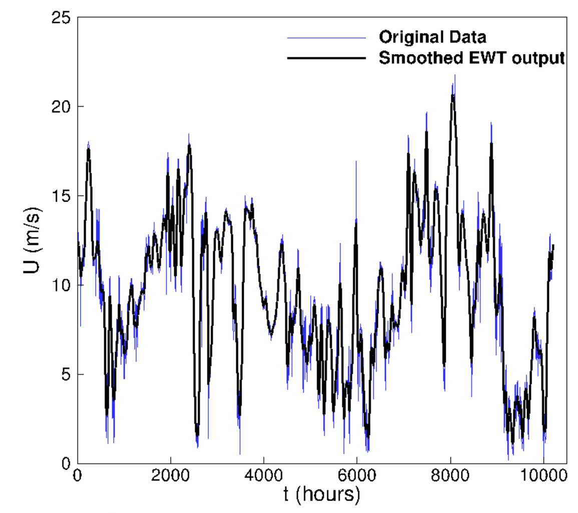


- RUNE was a near-shore experiment conducted at the west coast of Denmark.
- **Lidar measurements**
  - **Dual-Doppler scans**
  - **Performed by 2 lidars at positions 1 and 3**
- **Numerical simulations**
  - **WRF model v3.6**

Results

Data Pre-processing:

The WRF data was pre-processed using empirical wavelet transform to smooth the given wind speed time-series (ensure the data sequence is differentiable).

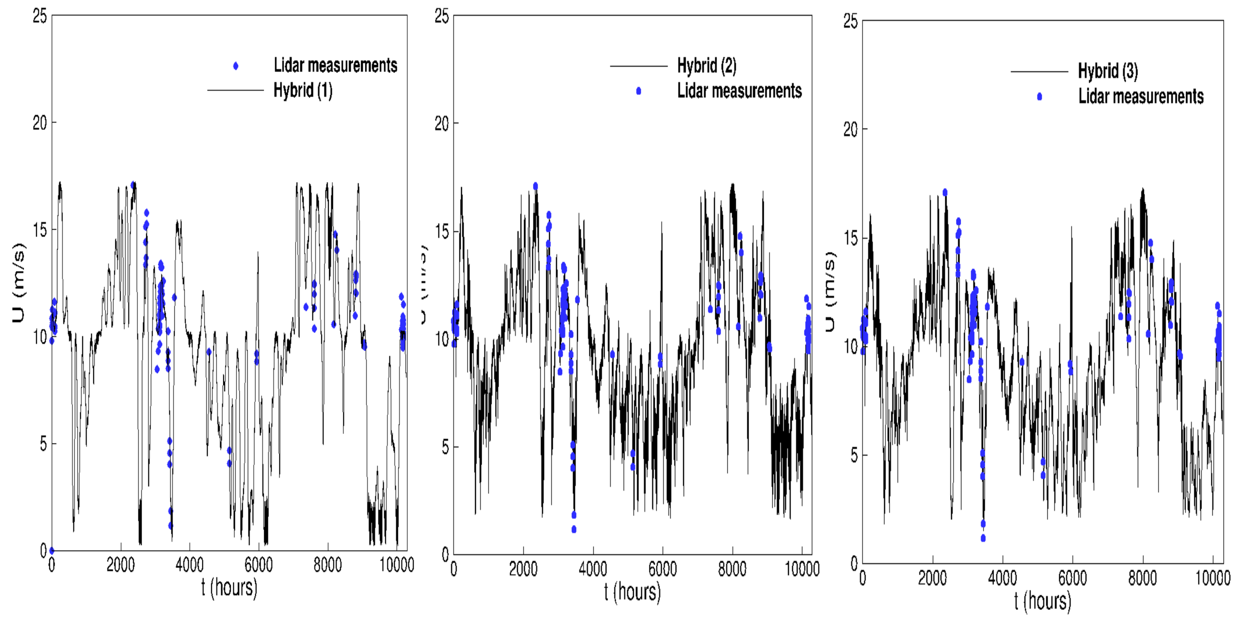


EWT processing
Original WRF (blue) and smoothed signal of wind speed at furthest onshore point.

Temporal Fusion:

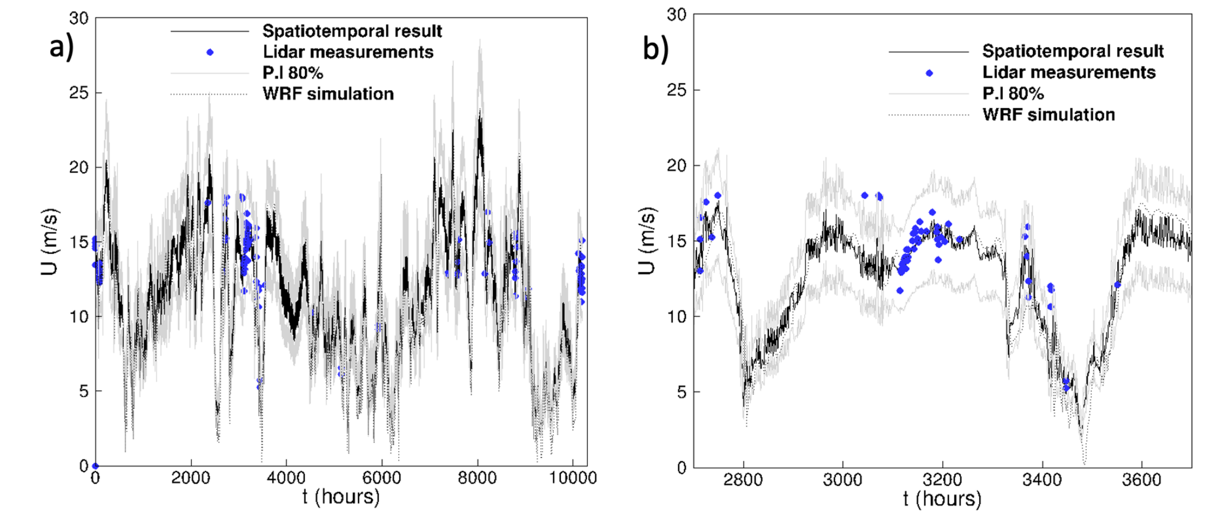
Fusion of continuous WRF and intermittent lidar:

- Hybrid (1): WRF + lidar (wind magnitude)
- Hybrid (2): WRF, its 1^{st} and 2^{nd} derivatives + lidar (wind magnitude)
- Hybrid (3): WRF, its 1^{st} and 2^{nd} derivatives + lidar, with EWT and two horizontal velocity components.



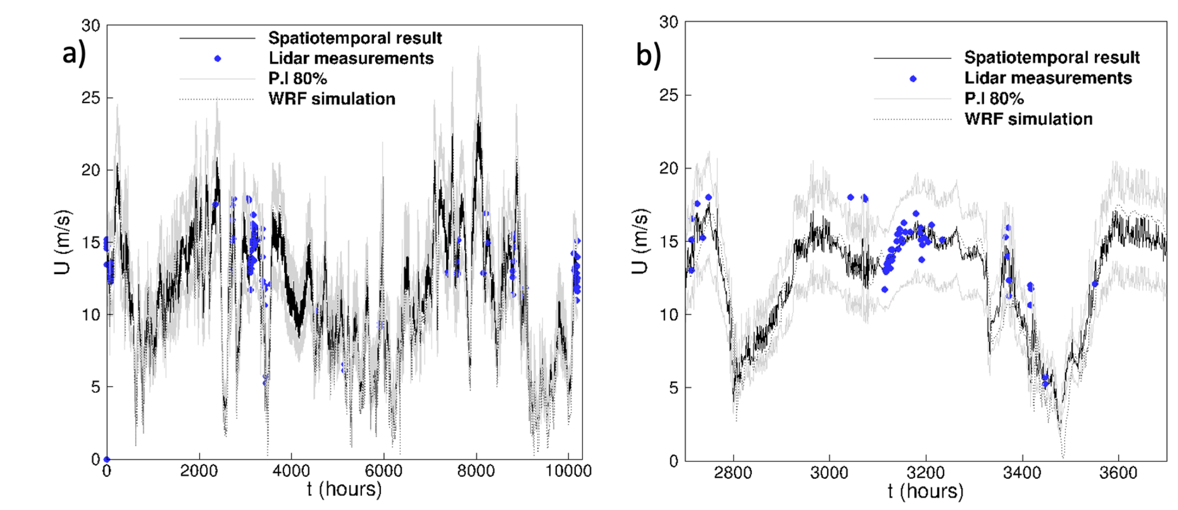
Spatial Fusion:

Extrapolation from onshore wind to offshore wind:



Spatio-temporal fusion continuous and accurate result
The combination of multi-fidelity GPR and NARX, generates a continuous high-fidelity time-series. That compared to WRF simulations is more precise with a lower RMSE.

Spatial-temporal Fusion:



The intermittent measurements at the most onshore point is used to estimate the wind at the most offshore point by exploiting the numerical data.

Conclusion

- In this work, we performed data fusion of WRF (low-fidelity) and lidar (high-fidelity) data in time and space to obtain a single step spatial-temporal fusion.
- For time domain predictions, using an effective smooth transform and increasing the number of useful additional information, shows a major drop in the RMSE.
- Space domain data fusion, can generate more accurate offshore results than WRF and doesn't require expensive equipment.
- Spatial-temporal fusion performs better than WRF simulations and requires less time.
- The method is found to be on a promising direction for use of reconciliation of different levels of data fidelity at different time horizons and locations.

References

For more details on the work showcased in this case study see the following publications:

- *R. Floors, A. Pe˜na, G. Lea, N. Vasiljevic, E. Simon, and M. Courtney. The RUNE experiment–a database of remote-sensing observations of near-shore winds. Remote Sens., 8:884–899, 2016.*
- *Floors R, Hahmann A.N, Pena A. Evaluating Mesoscale Simulation of the Coastal Flow Using Lidar Measurements. Journal of Geophysical Research: Atmospheres 2018;2718-2736-123.*

Acknowledgements

This project has received funding from the European Union Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 777717 and the future and emerging technologies programme with agreement No. 828799.