Predicting In-situ Wind Speed using Underwater Acoustics and Learning-Based Variational Data Assimilation

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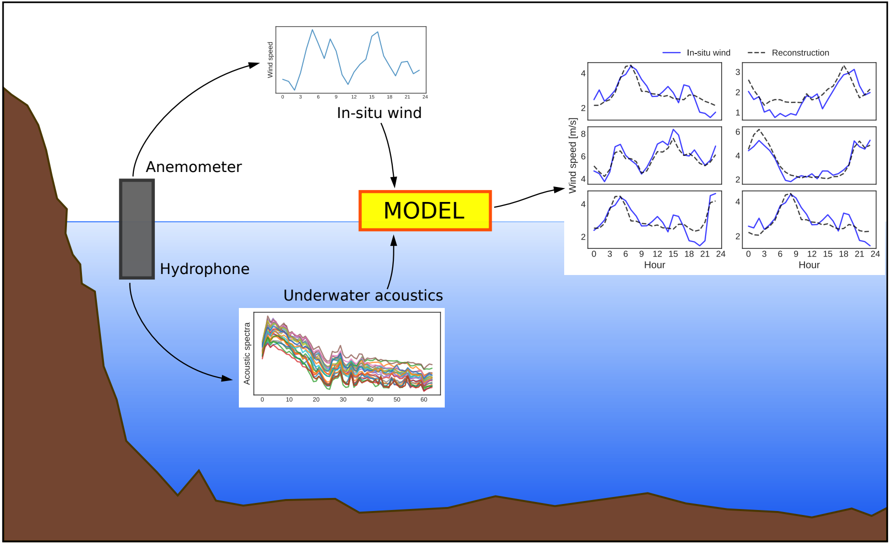
Objective



Anemometer
Hydrophone
Wind speed
In-situ wind
MODEL
Underwater acoustics
Acoustic spectra
In-situ wind
Reconstruction
Wind speed [m/s]
Hour
Hour

Outline

Objectives of the presentation

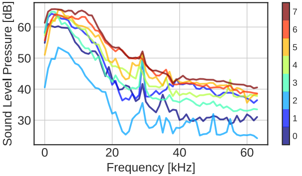
- Address a **data-driven variational data assimilation framework** to solve this inverse problem
- Discuss the viability of a **multi-modal approach** using both underwater acoustic data and synthetic wind speed data

Contents

- Data sets
- The 4DVarNet model
- Results

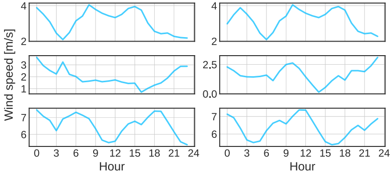
Underwater Passive Acoustics

- Acoustic spectra
- Discontinuous underwater ambient noise sampling
- FFT to project acoustic signal to frequency domain (64 bins)



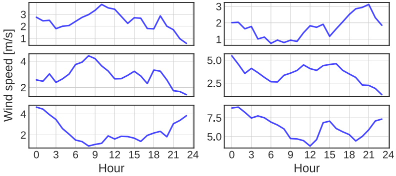
ECMWF wind speed

- Reanalyses
- Obtained with the integration of the 4DVar scheme
- Hourly resolution

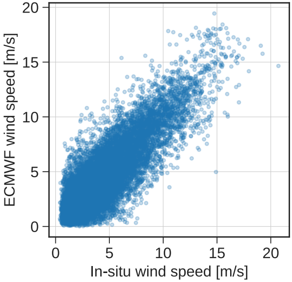


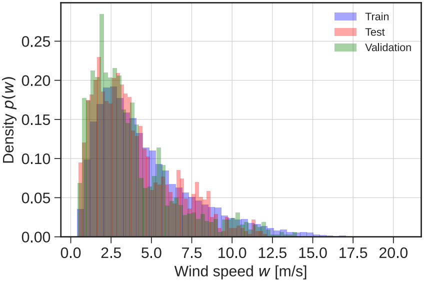
In-situ wind speed

- Wind measurements
- Hourly resolution
- Physically co-located with UPA hydrophone



In-situ and ECWMF wind speed values





ECMWF vs. In-situ wind speed

R^2 score : 0.71
RMSE : 1.71 m/s

Statistics [m/s]

Train set	Test set	Val set
Min : 0.4	Min : 0.48	Min : 0.41
Max : 20.71	Max : 12.15	Max : 14.02
Mean : 4.59	Mean : 3.88	Mean : 3.75
Std : 2.98	Std : 2.44	Std : 2.66

The 4DVarNet[1] model

Model based on the 4DVar Data Assimilation scheme + Deep Learning concepts

[1] Fablet, R., Chapron, B., Drumetz, L., Mémin, E., Pannekoucke, O., & Rousseau, F. (2021). Learning variational data assimilation models and solvers. Journal of Advances in Modeling Earth Systems, 13, e2021MS002572. https://doi.org/10.1029/2021MS002572

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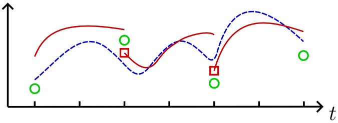

Reanalysis : optimal x_t given by 4DVar

Model $\mathcal{M}$ integration : $x_t = \Phi(x;t)$

True state evolution according to $\frac{\partial x(t)}{\partial t} = \mathcal{M}(x;t)$

Observation $y_t = \mathcal{H}(x_t)$

Data validate the model !!!

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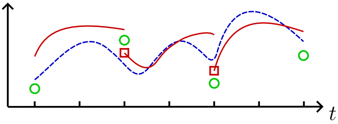

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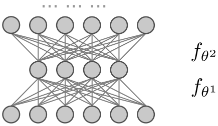
- Trainable Neural Network Modules



$\mathcal{M} := f_{\theta^1} \circ \cdots \circ f_{\theta^n}$	Non-linear cascade
$y = \mathcal{M}(x)$	Input-output map
$\theta = \arg\min_\theta \mathcal{C}(x, y)$	Parameters optimization

Data DEFINE the model !!!

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The 4DVarNet model

Model based on the 4DVar Data Assimilation scheme + Deep Learning concepts

- State-space model

$$\begin{cases} \dfrac{\partial x(t)}{\partial t} & = & \mathcal{M}(x;t) \\ y & = & \mathcal{H}(x;t) \end{cases} \xrightarrow{\text{Discretize}} \begin{cases} x_t & = & \Phi(x;t) & \text{Dynamical equation} \\ y_t & = & \mathcal{H}(x_t) & \text{Observation equation} \end{cases}$$

- Variational cost : minimize to get the state variable x

$$U_\Phi(x, y; \Omega) = \underbrace{\boxed{\|y - \mathcal{H}(x)\|_\Omega^2}}_{\text{Data fidelty}} + \underbrace{\boxed{\|x - \Phi(x)\|^2}}_{\text{Physics Compliance}}$$

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4DVarNet proposal

- Neural network parametrization of Φ
- Neural network parametrization of the gradient solver Γ

$$\begin{cases} \delta^{(k+1)} & = & \Gamma(\nabla_x U_\Phi) \\ x^{(k+1)} & = & x^{(k)} - \delta^{(k+1)} \end{cases}$$

4DVar

- Explicit knowledge of the observation operator

$\mathcal{H} : x \to y$???

- Integration of the physical prior
  Requires conceptual and computational effort

$\mathcal{M} : x \to x$!!!

4DVarNet

- $\mathcal{M}$ is trainable
- $\mathcal{H}$ is trainable

NN-parametrization advantages :

- Computational Tensor Algebra
- Hardware Acceleration
- Automatic differentiation

- Flexible operators representation
- Trainable gradient solver

Models

Physical prior $\Phi : x \to x$

- 1D *Convolutional* Auto-encoder architecture
- Structure, having hidden space dimension of 20, is

$$\begin{cases} \text{Encoder} & : & \text{input\_size} \to 128 \to 20 \\ \text{Decoder} & : & 20 \to 128 \to \text{input\_size} \end{cases}$$ (Latent space)

Gradient solver $\Gamma : x \to x$

- *Convolutional* Long-Short Term Memory (LSTM) network
- The hidden cell dimension is 100

Experimental setup

Models

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Data

Each time series X^γ, $\gamma = \{\text{UPA}, \text{ ECMWF}, \text{ Situ}\}$ is formatted in such a way that

$$\dim(X^\gamma) = (M,\, T,\, N_\gamma)$$

I.e. the dataset is a collection of M N_γ-variate time series of length T $\equiv 24$ in this case

Multi-modal approach

With multi-modal machine learning

- Heterogeneous datasets should be used
- The complementary information contained in each modality can be exploited

In our scope

- UPA and ECMWF **both** convey useful information for in-situ wind speed

$$y^\alpha = \left[y^{\text{UPA}}, y^{\text{ECMWF}}\right] = \text{concat}\left(y^{\text{UPA}}, y^{\text{ECMWF}}\right)$$

- We have a multi-modal higher-dimensional latent state, with $y^\beta \leftarrow y^{\text{Situ}}$

$$x = \left[x^\alpha, x^\beta\right] = \text{concat}\left(x^\alpha, x^\beta\right); \quad \dim(x) = N^\alpha + N^\beta$$

- A *linear observation operator* $\mathcal{H}$ provides observations y^α **only**

$$y = \left[y^\alpha, 0 \cdot y^\beta\right] = \mathcal{H}(x); \quad \dim(y) = N^\alpha + N^\beta$$

- State-of-the-art[2] : Ensemble regression models

$$y_t^{\alpha} \mapsto u_t^{\beta}$$

- 4DVarNet approach : Prediction of **time series** of wind speed

$$\{y_t^{\alpha};\ t \in \mathbb{T}_k\} \mapsto \{x_t;\ t \in \mathbb{T}_k\}\,; \quad \text{with } \mathbb{T}_k \subset \mathbb{T} \text{ and } \cup_k \mathbb{T}_k = \mathbb{T}$$

[2] W. O. Taylor, M. N. Anagnostou, D. Cerrai and E. N. Anagnostou, "Machine Learning Methods to Approximate Rainfall and Wind From Acoustic Underwater Measurements (February 2020)," in IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 4, pp. 2810-2821, April 2021, doi: 10.1109/TGRS.2020.3007557

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Thus we define

$$y_t^\alpha \mapsto y_t^\beta \qquad \textbf{Time-independent} \text{ case}$$

$$\{y_t^\alpha;\ 0 \leq t < T\} \mapsto \{y_t^\beta;\ 0 \leq t < T\} \qquad \textbf{Time-dependent} \text{ case}$$

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Results — Assessment

- Performance metrics : (RMSE) restricted on the observation domain Ω^β

$$E(y^\beta, \hat{x}^\beta) = \|y^\beta - \hat{x}^\beta\|^2_{\Omega^\beta}$$

- *Model average* of 10 model runs

$$\begin{cases} u & = & \mathrm{median}\left(\{\hat{x}^\beta_j\}_{j=1}^{10}\right) \\ E(y^\beta, u) & = & \|y^\beta - u\|^2_{\Omega^\beta} \end{cases}$$

- Evaluate 4DVarNet performance and robustness for three test cases
  1. Reconstruction from the complete dataset
  2. Reconstruction with irregular sampling
  3. k-steps-ahead forecast

Table 1: RMSE metrics for time independent case.

Model	Metrics in m/s		
	RMSE	Mean ± std	n-Median
ECMWF 4DVarDA	1.71	–	–
SAR GMF images	1.33	–	–
SPL-full regression	1.16	–	–
CatBoost	0.95	–	–
Random Forest	0.97	–	–
FC-AE	–	0.98 ± 0.03	0.95

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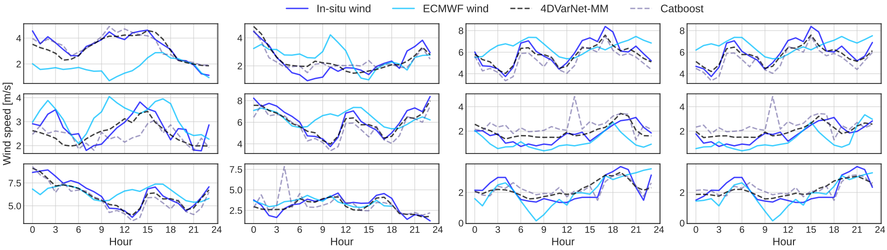
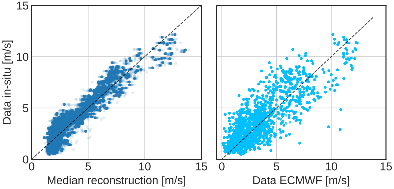
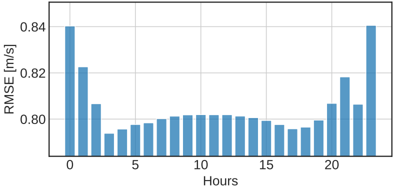
Table 2: Results for single and multi-modal settings, time dependent case. The relative gains are referred to the best baseline model, that is the FC-AE.

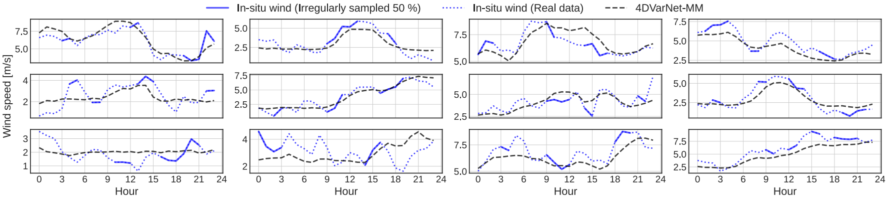
Model	Metrics in m/s		Relative gain
	Mean ± std	n-Median	η [%]
FC-AE	0.97 ± 0.04	0.92	3.2
Conv-AE-UPA	0.94 ± 0.04	0.88	7.4
4DVarNet-UPA 5 iter	0.91 ± 0.02	0.87	8.4
4DVarNet-UPA 10 iter	0.89 ± 0.04	0.84	11.6
Conv-AE-UPA+ECMWF	0.88 ± 0.02	0.83	12.6
4DVarNet-UPA+ECMWF 5 iter	0.85 ± 0.03	0.81	14.7
4DVarNet-UPA+ECMWF 10 iter	$\mathbf{0.84 \pm 0.02}$	**0.80**	**15.8**

Results — Reconstruction









Examples of reconstructions, sampling rate $r = 50\%$, RMSE $E = 0.89\ m/s$

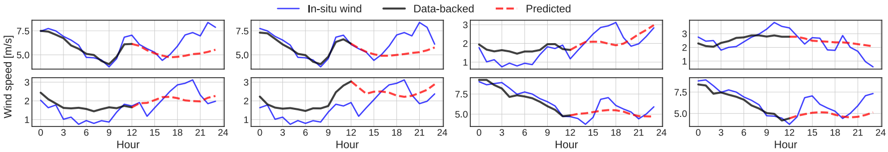
Method

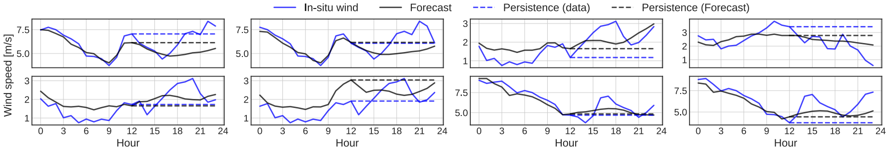
$$\{y_t^\alpha\}_t \leftarrow \{y_t^\alpha\}_t \odot \Omega$$

Ω masks a given fraction r of the T timesteps

r %	Metrics in m/s Mean $\pm$ std	n-Median
10	0.85 $\pm$ 0.02	0.80
20	0.87 $\pm$ 0.02	0.81
30	0.90 $\pm$ 0.02	0.83
40	0.92 $\pm$ 0.02	0.83
50	0.98 $\pm$ 0.02	0.89
60	1.01 $\pm$ 0.02	0.91
70	1.07 $\pm$ 0.03	0.96
80	1.17 $\pm$ 0.03	1.08
90	1.27 $\pm$ 0.03	1.21

Results — k-steps-ahead Forecast ($k = 12$)





Method

$$\{y_t^\alpha\}_t \leftarrow \{y_t^\alpha\}_t \odot \Omega$$

Ω masks a whole sub-sequence of the time steps

RMSE $[m/s]$ for interval $[12, 24)$	
$E(\hat{x}^\beta,\, y^\beta)$	1.43
$E(P\, y^\beta,\, y^\beta)$	1.80
$E(P\, \hat{x}^\beta,\, y^\beta)$	1.74

$P\,u$ is the Persistence of the signal u after the last sampling point

Conclusions

Take-home message

- Improved predictive performance of wind speed wrt to state-of-the-art models
- Reconstruction of time series of wind speed, not only a model value-to-output
- The potential of the multi-modal approach

Future work

- Inspect further the « forecast » aspect
- Integration of spatial dimension
- Super-resolution task