DeepFarm: Deep Generative Modelling for Wind Farms

Conference Poster

Author(s):
Mylonas, Charilaos; Abdallah, Imad; Chatzi, Eleni

Publication date:
2019-06

Permanent link:
https://doi.org/10.3929/ethz-b-000385323

Originally published in:
https://doi.org/10.13140/RG.2.2.22360.24322

Funding acknowledgement:
679843 - Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines (EC)

DeepFarm: Deep Generative Modelling for Wind Farms

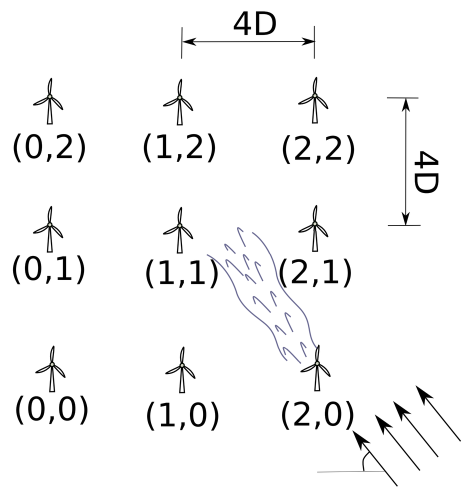
Charilaos Mylonas* , Imad Abdallah and Eleni Chatzi
Structural Mechanics and Monitoring, Institute of Structural and Environmental Engineering ETH Zürich, Switzerland
mylonas@ibk.baug.ethz.ch

1. Introduction

Condition monitoring and remaining useful life prediction of wind turbines relies on statistical modeling of operational data. Supervisory Control and Data Acquisition (SCADA) systems, contain summary statistics on quantities of interest. Monitoring data of wind turbines are affected by a complex interaction of environmental factors, control, and aerodynamics. When placed in a farm, wind turbines produce traveling vortices (wakes) that lower the power production and increase mechanical vibrations of down-stream turbines. A data-driven methodology is proposed, that relies on deep neural networks and variational inference for capturing such effects. Namely a **Variational Autoencoder (VAE)** is employed for the statistical modeling of condition monitoring data of wind farms. The methodology is employed on full aero-servo-elastic simulations of a small fictitious windfarm.

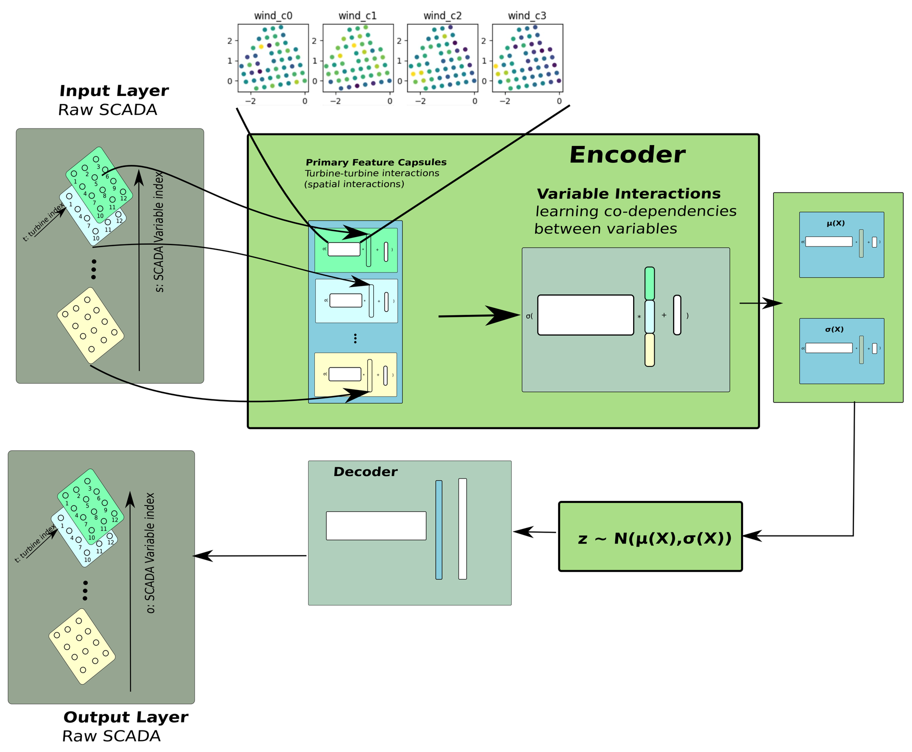
2. Wind Farm DWM Simulations

Wind velocity inflow fields are created according to the Kaimal turbulence model. The wake effect is approximated by the **Dynamic Wake Meandering (DWM)** model. DWM model is an engineering wake model designed to physically model the wake deficit evolution and the unsteady meandering that occurs in wind turbine wakes, including small- and large-scale turbulence structures.



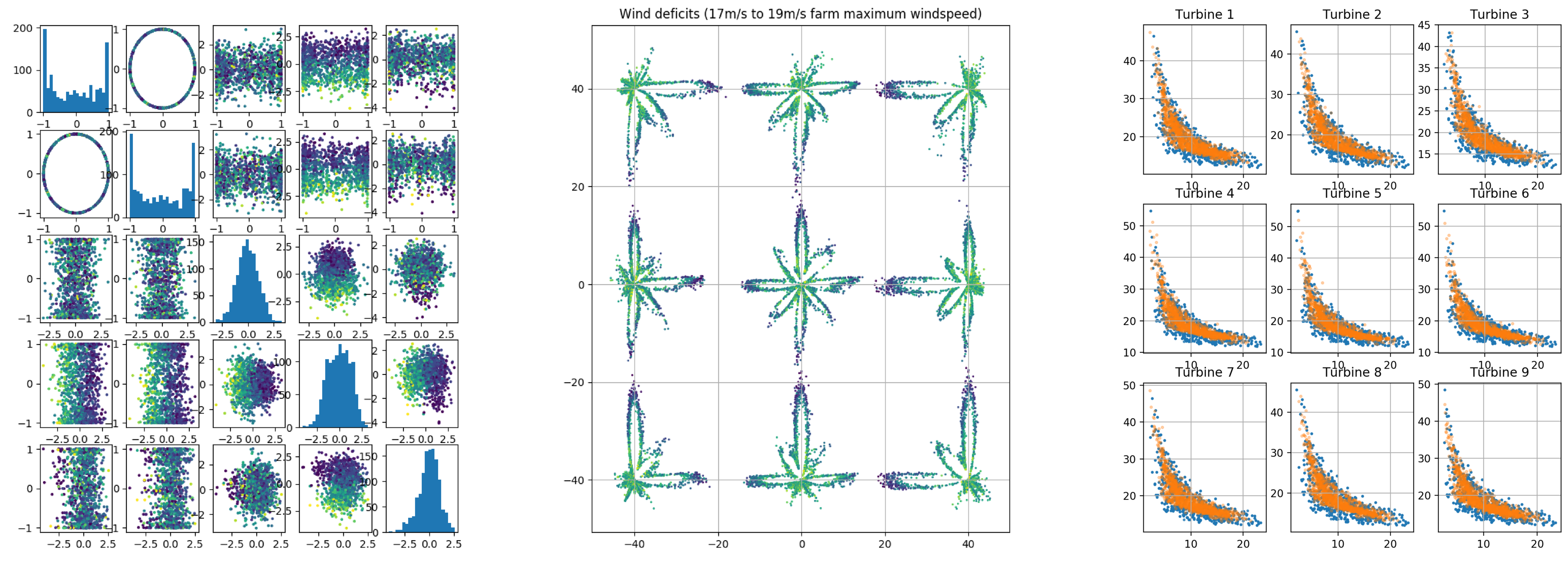
3. Structure of the VAE

The SCADA readings are treated as 2-way tensors (9 x 5) with one dimension corresponding to the turbine index and the other to the SCADA channel. The network is structured so that the spatial dependence between turbines is learned in sub-networks of the encoder.



4.Sampling the VAE

By conditioning the decoder (recognition network) during training with some a-priori known influencing factors, such as farm-mean wind speed, and farm-mean wind orientation, and by replacing the data-dependent approximate posterior with the assumed spherical Gaussian prior we can perform conditional sampling from the VAE.



Left: Learned latent space, colored by farm-mean wind speed. **Middle:** Per-turbine visualization of samples from the learned distribution of wind deficits (marginalized w.r.t. wind-orientation and conditioned on a range of mean farm wind speeds) **Right:** Simulated (blue) and VAE-sampled (orange) joint distribution of 10-minute mean wind speed [m/s] turbulence intensity[-].

5. Training the VAE

The VAE objective reads [1],

$$\mathcal{L}(\boldsymbol{\phi},\boldsymbol{\theta};\mathbf{x}^{(i)}) = -\beta D_{KL}(q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^{(i)})||p_{\boldsymbol{\theta}}(\mathbf{z})) + \mathbb{E}_{q_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x}^{(i)})}\left[\log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}|\mathbf{z})\right]$$

The first term is a measure of similarity between $q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^{(i)})$ and $p_{\boldsymbol{\theta}}(\mathbf{z})$ (KL divergence). The second term is a reconstruction loss. Parameter β is a scalar controlling the trade-off between reconstruction accuracy and low KL divergence. Low-variance single-sample estimates of the gradient through the stochastic layer, $q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^{(i)})$ are achieved using the re-parametrization trick [1]. Heuristics were necessary to train with $q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x})$ close to $p_{\boldsymbol{\theta}}(\mathbf{z})$ (low KL) and good reconstruction performance. **(1)** using mini-batching, even though it is not necessary for the scale of the data, **(2)** annealing the KL term in the objective **(3)** using a small learning rate and a burn-in period.

6. Applications and Future Work

In [2] we demonstrated that VAEs can exploit the non-linear dependencies between variables for joint distribution modeling with a relatively small amount of samples. Future applications are going to be focused on dealing automatically with learning the effect of discrete states (e.g. automatic unwinding related yaw misalignment and excessive vibration related emergency stops), applying the methodology on SCADA datasets of real wind farms. Future technical extensions considered, include *Normalizing flows* for more flexible posteriors or exact likelihood inference, and incorporation of recent advancements on optimization for VAEs [3] and re-parametrizations for categorical distributions. Concrete applications include robust statistical condition monitoring, interpretation of high-dimensional stochastic simulation data, imputation of missing monitoring data, and quantification of aleatory uncertainty on cyclic load estimates from SCADA summary statistics.

7. References

[1] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

[2] Charilaos Mylonas, Imad Abdallah, and EN Chatzi. Deep unsupervised learning for condition monitoring and prediction of high dimensional data with application on windfarm scada data. In *Model Validation and Uncertainty Quantification, Volume 3*, pages 189–196. Springer, 2020.

[3] Danilo Jimenez Rezende and Fabio Viola. Taming vaes. *arXiv preprint arXiv:1810.00597*, 2018.

8. Ackgnowledgements

ERC Starting Grant **WINDMIL** (ERC-2015-StG #679843) on the topic of Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines.