Analog Ensemble Probabilistic Forecasting using Deep Generative Models

Alessandro Fanfarillo[1]

[1]National Center for Atmospheric Research

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Abstract

Deterministic Numerical Weather Prediction (NWP) models are the state-of-the-science models to provide reliable weather forecasts that provide indispensable actionable data to society. However, each NWP model run carry uncertainty caused by errors in initial conditions and assumptions in the model. As a result, probabilistic forecasts can be used to quantify and even correct the model bias. The Analog Ensemble (AnEn) technique uses a historical dataset of past deterministic forecasts and their associated observations to generate an ensemble of future outcomes. One of the main advantages of the AnEn technique, along with other related statistical ensemble techniques, is that it is not necessary to run multiple NWP runs by varying initial conditions or model settings. However, all these techniques require access to the entire historical dataset to generate analogs. Moreover, these techniques require reading the dataset for every forecast which is computationally expensive. In this work, the whole historical dataset is replaced by a model that has the capability to learn the Probability Density Function (PDF) of that dataset. Specifically, we utilize a Conditional Variational Autoencoder (CVAE) deep generative machine learning model in order to correct the wind speed forecasts of North American Mesoscale (NAM) forecasting system. As a result, we feed the values forecasted by the NWP model as a condition to our CVAE and generate an ensemble used to correct the forecasted value in constant time and with small memory usage. Initial results show that CVAE probabilistic performance is comparable to AnEn while CVAE can be up to 25 and 2 times smaller in memory and runtime, respectively, for 5 years of historical data.

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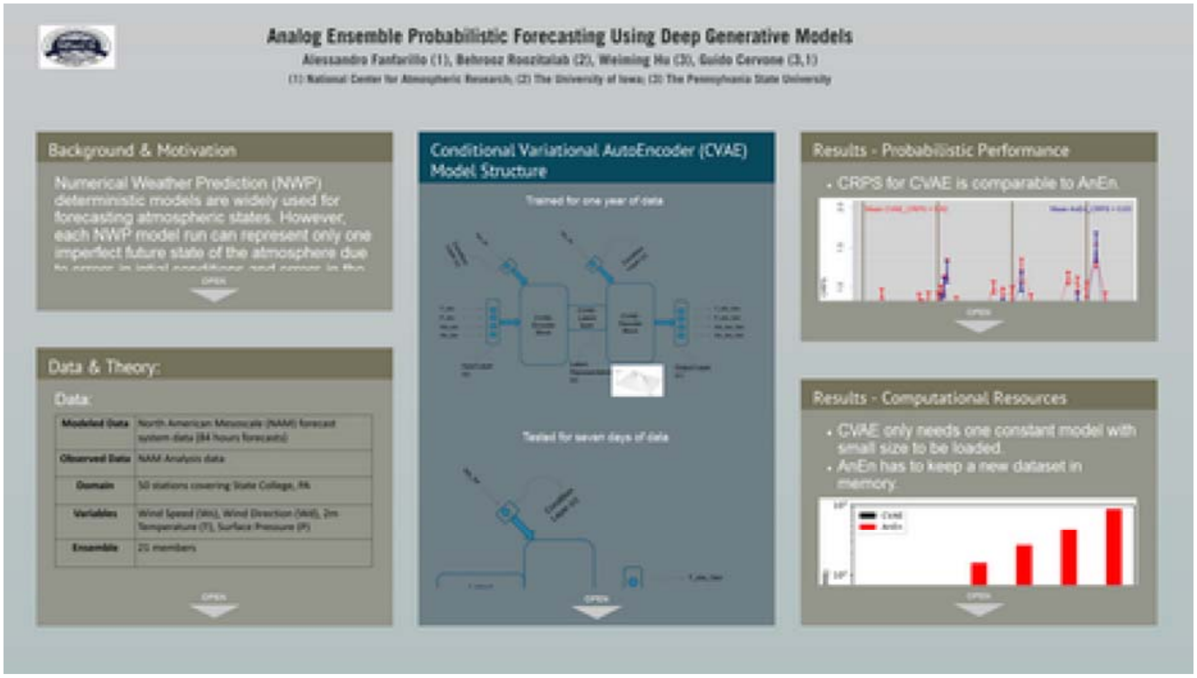


Alessandro Fanfarillo (1), Behrooz Roozitalab (2), Weiming Hu (3), Guido Cervone (3,1)

(1) National Center for Atmospheric Research; (2) The University of Iowa; (3) The Pennsylvania State University

PRESENTED AT:

BACKGROUND & MOTIVATION

Numerical Weather Prediction (NWP) deterministic models are widely used for forecasting atmospheric states. However, each NWP model run can represent only one imperfect future state of the atmosphere due to errors in intial conditions and errors in the model.
The Analog Ensemble (AnEn) is a probabilistic forecasting technique that corrects a future model forecast by using similar historical forecasts. The AnEn technique searches through the entire historical repository, which is computationally expensive. In this work, a Conditional Variational AutoEncoder (CVAE) generative machine learning model is proposed to correct the model forecasts using probability distribution of the historical datasets in constant time and with small memory usage.

Research Objectives:

- Explore the capabitliy of generatvie machine learning models in improving atmospheric forecasts compared to AnEn.
- Quantify the effect of using machine learning models on saving computational resources.

DATA & THEORY:

Data:

Modeled Data	North American Mesoscale (NAM) forecast system data (84 hours forecasts)
Observed Data	NAM Analysis data
Domain	50 stations covering State College, PA
Variables	Wind Speed (Ws), Wind Direction (Wd), 2m Temperature (T), Surface Pressure (P)
Ensemble	21 members

AnEn Conceptual Model:

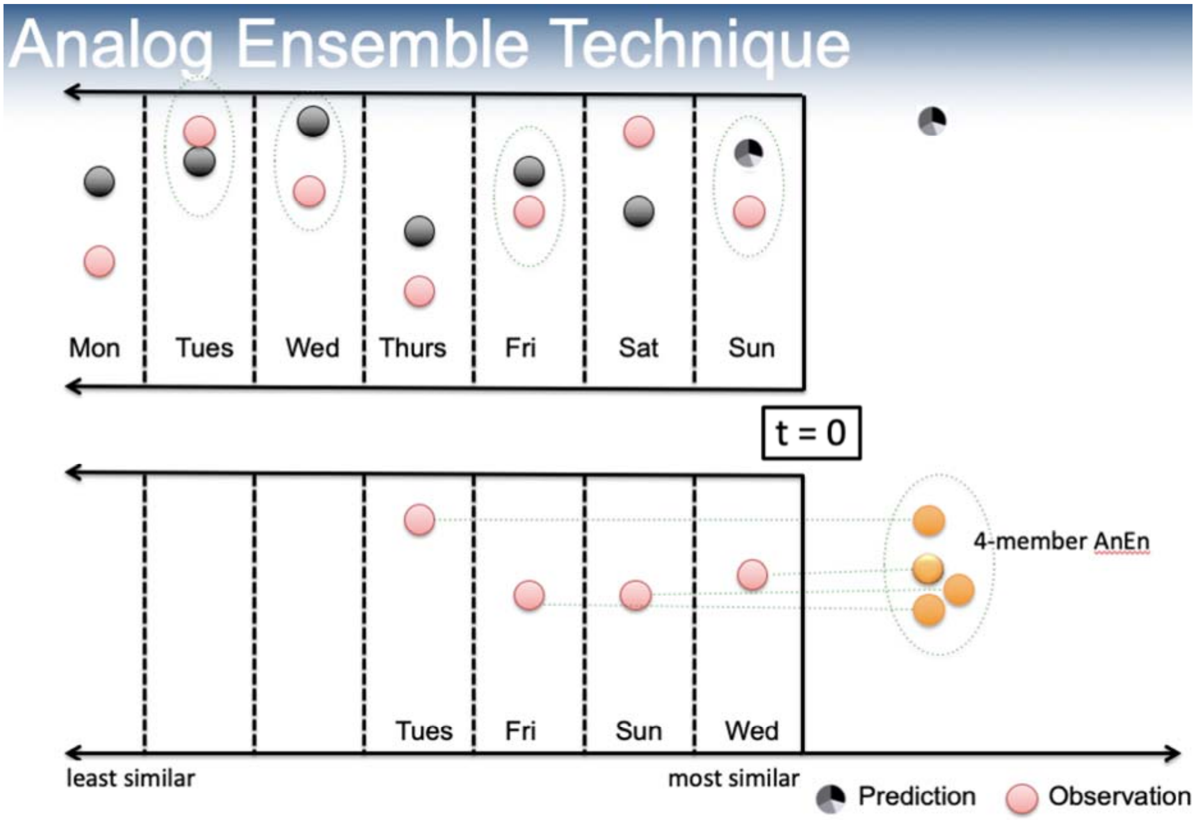


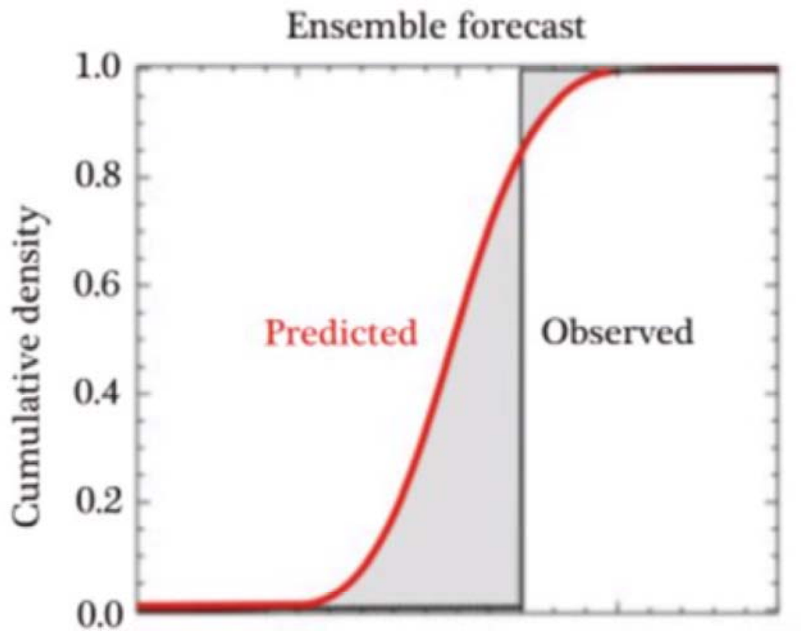
Figure credited to: Laura Clemente-Harding, Weiming Hu, Parallel Analog Ensemble Forecasts with Ensemble Toolkit on HPC, 2019 Software Engineering Assembly, NCAR, Boulder, CO, https://sea.ucar.edu/event/parallel-analog-ensemble-forecasts-ensemble-toolkit-hpc

CVAE Cost Function:

$$\log P_\theta(x|c) - D_{KL}(Q_\phi(z|x,c) \| P_\theta(z|x,c))$$
$$= \mathbb{E}_{z\sim Q}[\log P_\theta(x|z,c)] - D_{KL}(Q_\phi(z|x,c)$$
$$\| P_\theta(z|c))$$

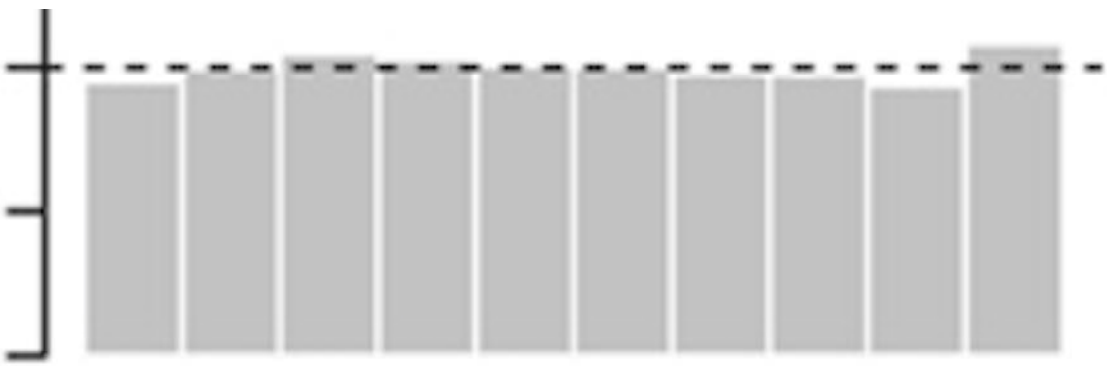
Evaluation Metrics:

- Continous Ranked Probability Score (CRPS):



$$S(F, o) = \int (F(z) - H(z - o))^2 dz$$

- Rank Histogram:

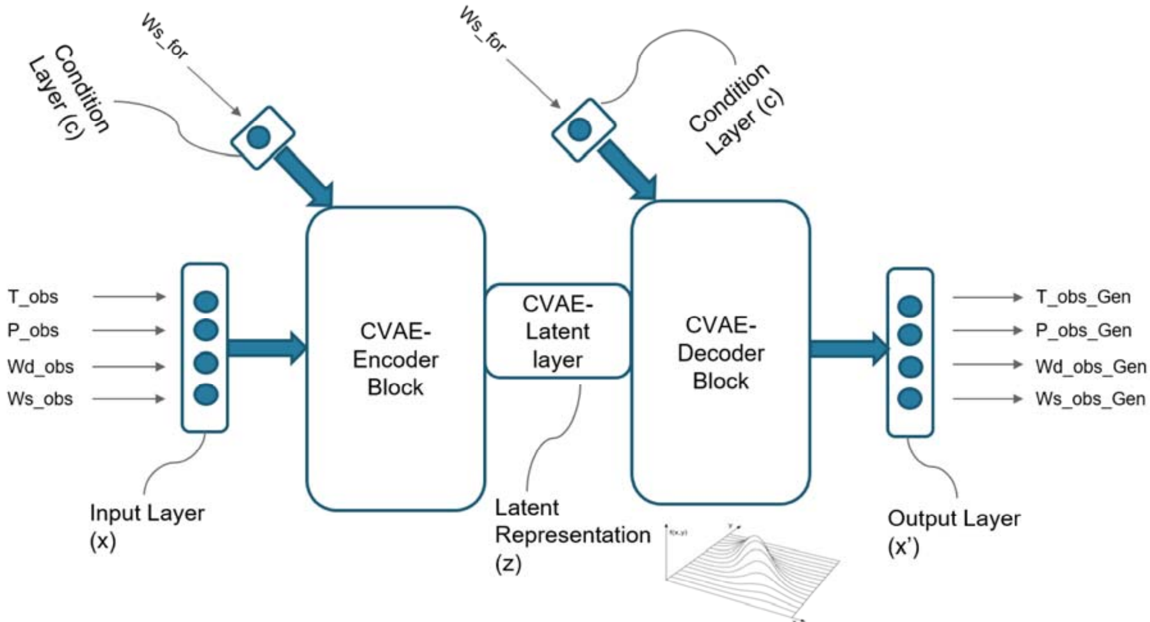


- Dispersion:

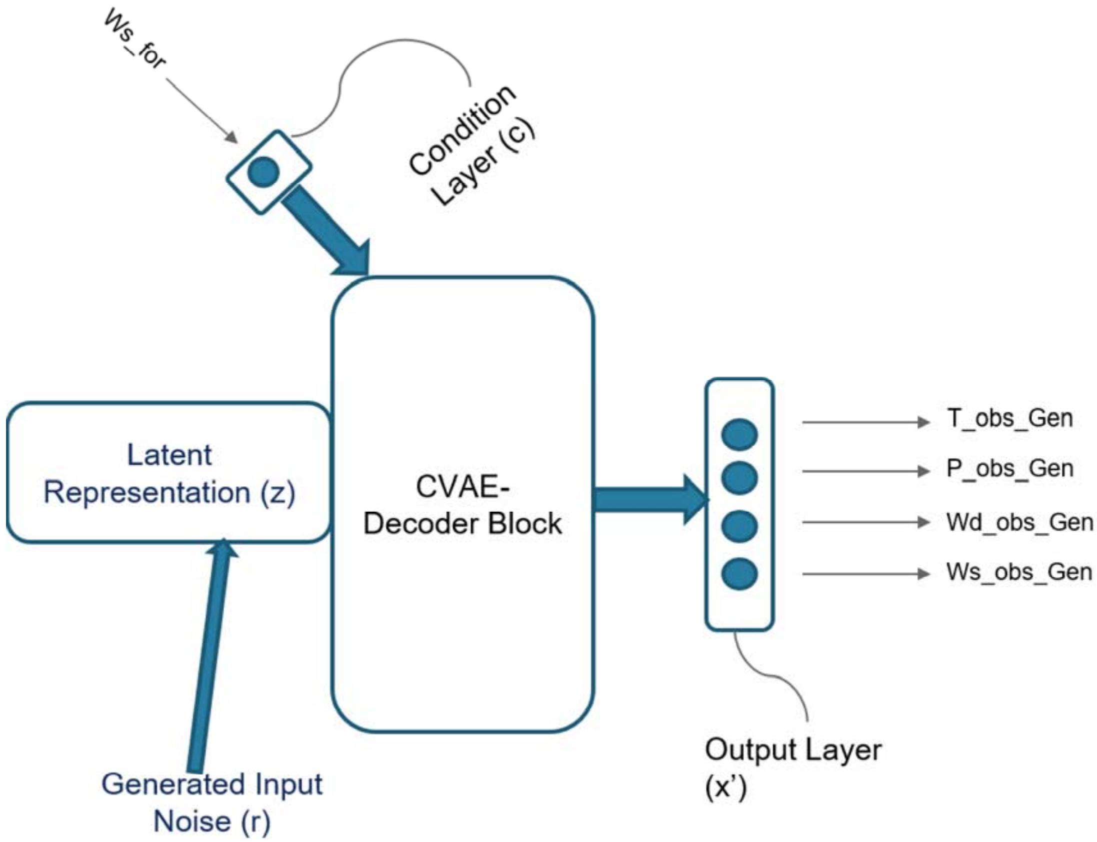
$$E[(x - x)^2] = \frac{m+1}{m} E[s^2]$$

CONDITIONAL VARIATIONAL AUTOENCODER (CVAE) MODEL STRUCTURE

Trained for one year of data

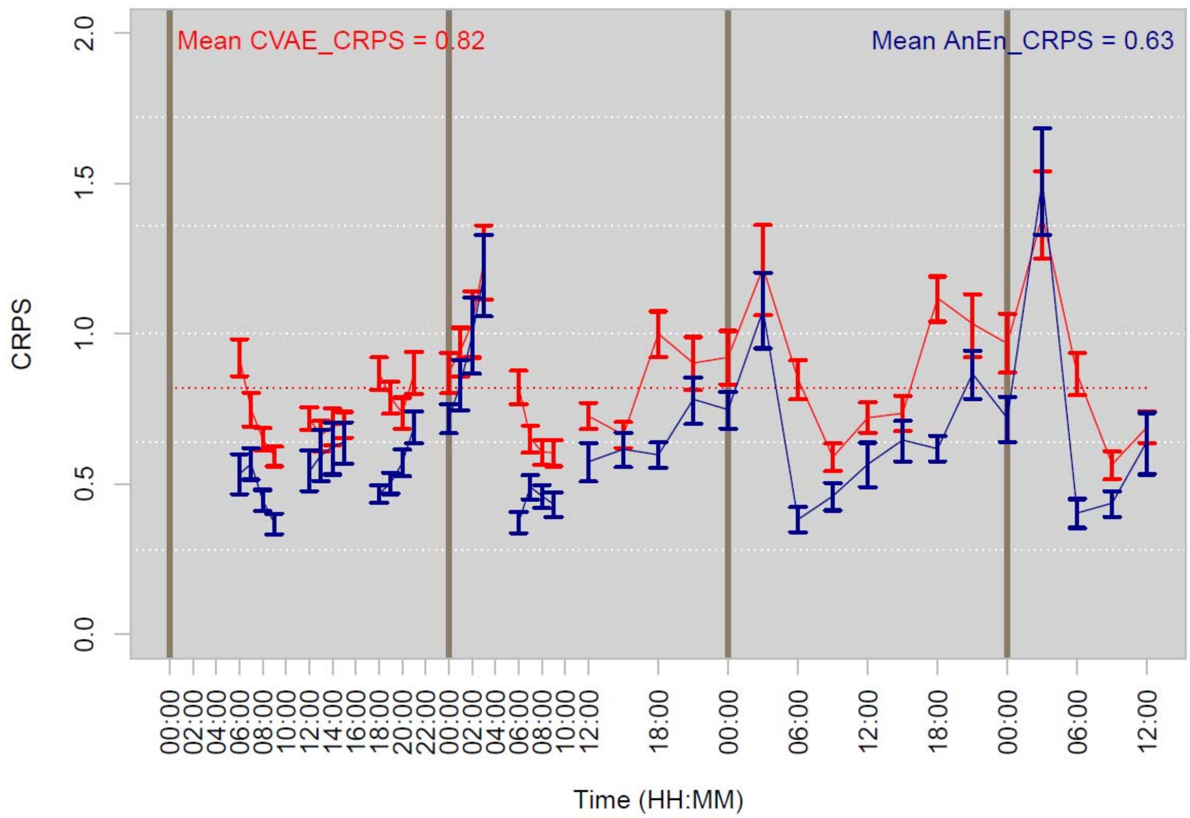


Tested for seven days of data

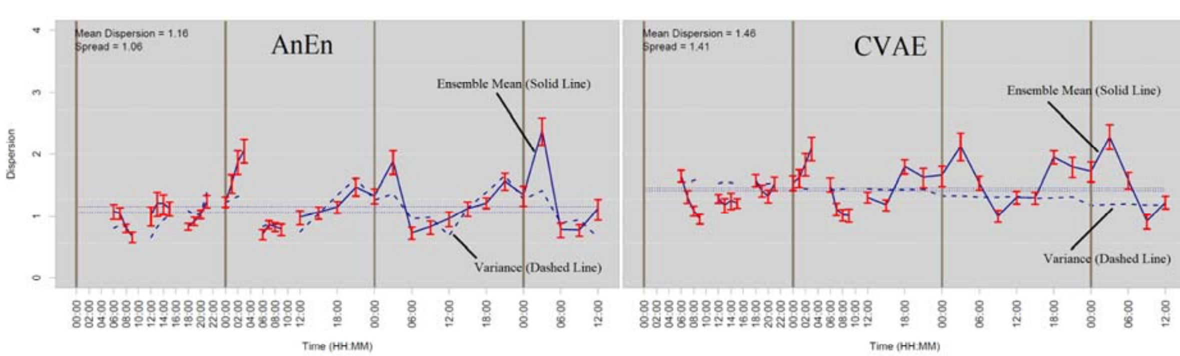

Ws_for
Condition Layer (c)
Latent Representation (z)
CVAE-Decoder Block
Generated Input Noise (r)
T_obs_Gen
P_obs_Gen
Wd_obs_Gen
Ws_obs_Gen
Output Layer (x')

RESULTS - PROBABILISTIC PERFORMANCE

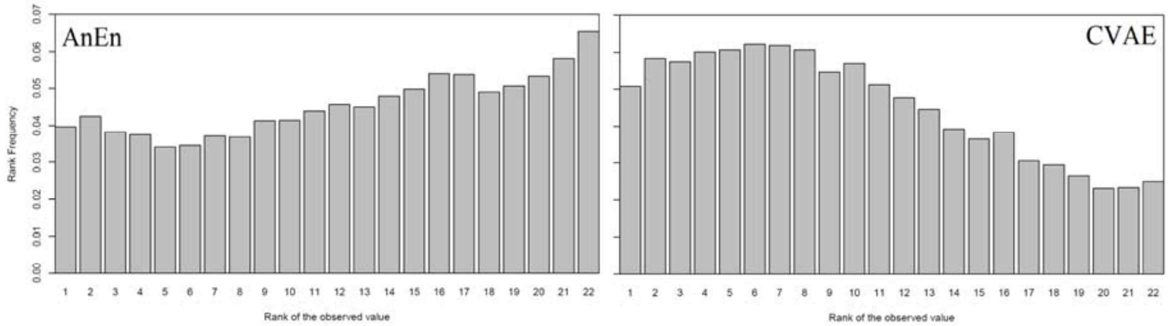
- CRPS for CVAE is comparable to AnEn.



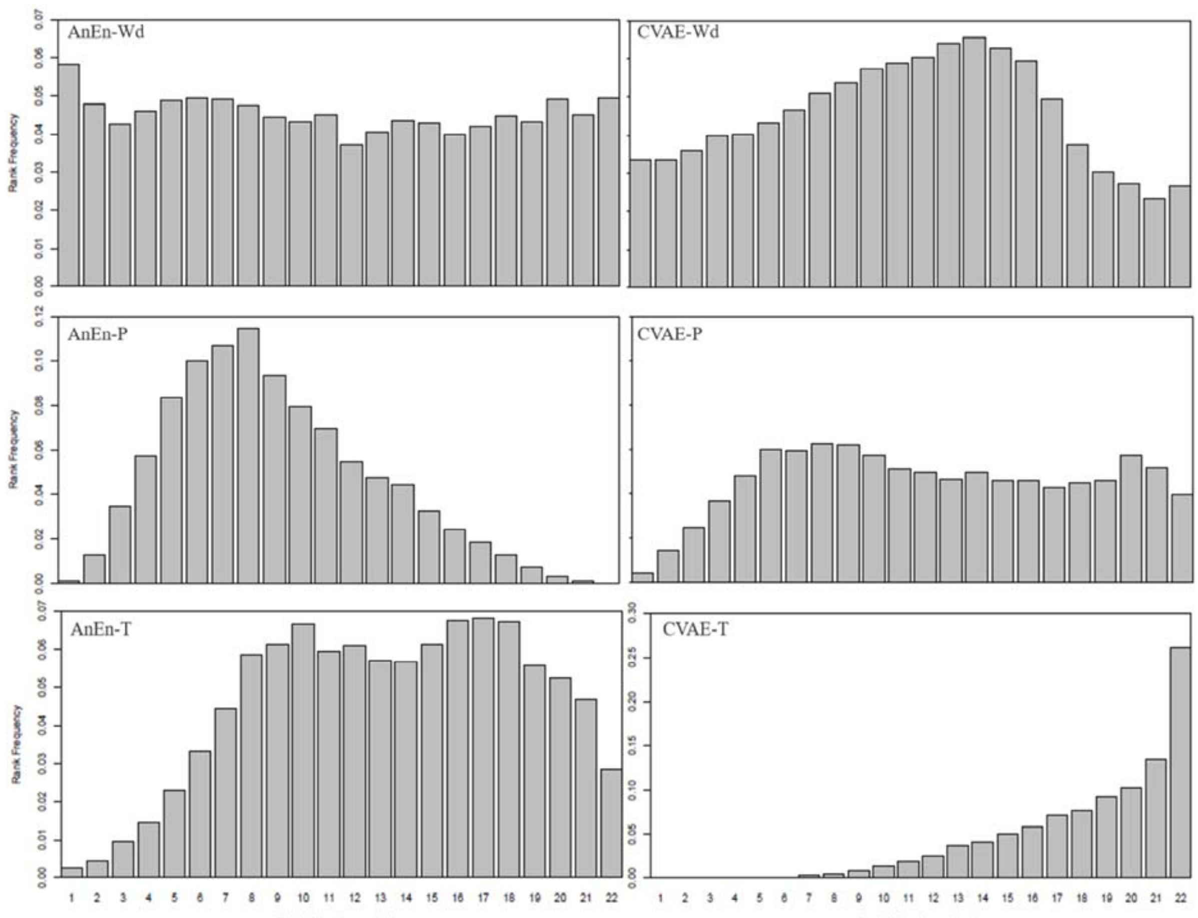
- CVAE forecasts have higher Bias (Mean Dispersion)
- Differences between Mean Dispersion and Variance is close for both methods.



- CVAE forecasts are as reliable as AnEn.

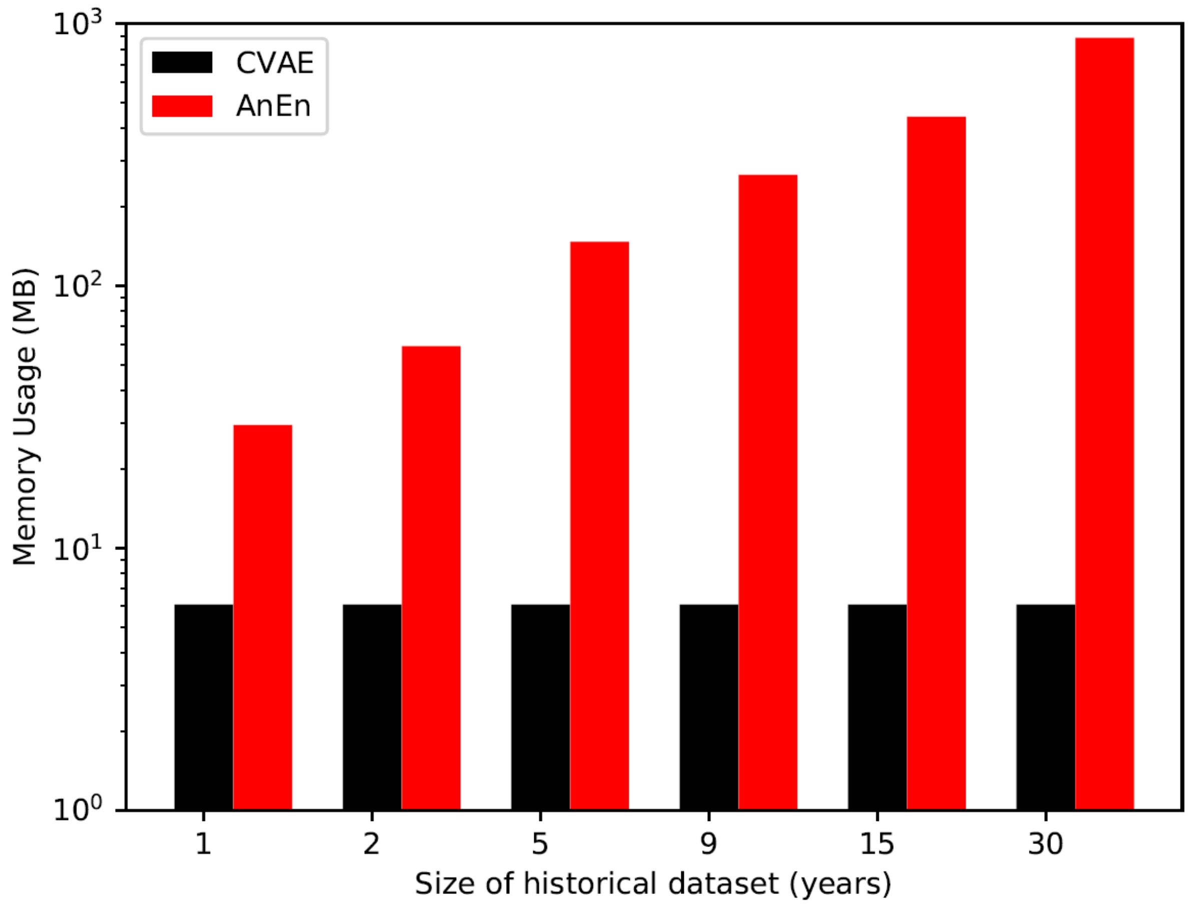


- However, current model is using wind speed as the only condition and hence the prediction results for other variables are not relieble enough.

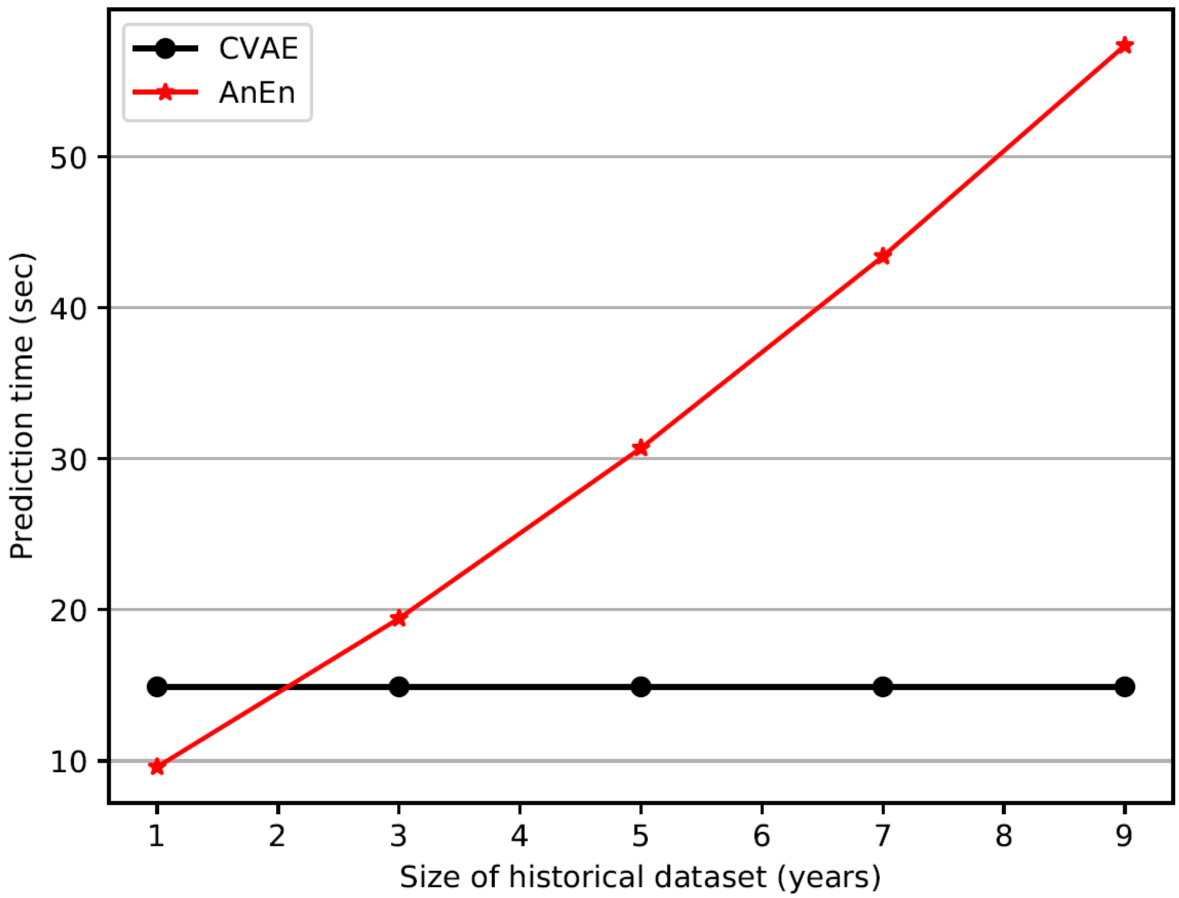


RESULTS - COMPUTATIONAL RESOURCES

- CVAE only needs one constant model with small size to be loaded.
- AnEn has to keep a new dataset in memory.



- CVAE uses one constant model with predefined parameters for perdictions.
- AnEn has to search the physical dataset.



Acknowledgments:

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