

# **Machine Learning Approach for Probabilistic Wind Power Forecasts with Discrete Probability Density Function**

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# Motivation

- Detailed power forecast error information often requested
- Our standard Deep Neural Network (DNN) based method provides only StD estimate
- Calibration of NWP ensemble models causes additional complexity
- Usage of NWP ensembles with DNN still unclear

## **But:**

- Analog Ensemble (AnEn) method shows there is uncertainty information in the historical data record
- Different NWP models can be combined to provide additional uncertainty information

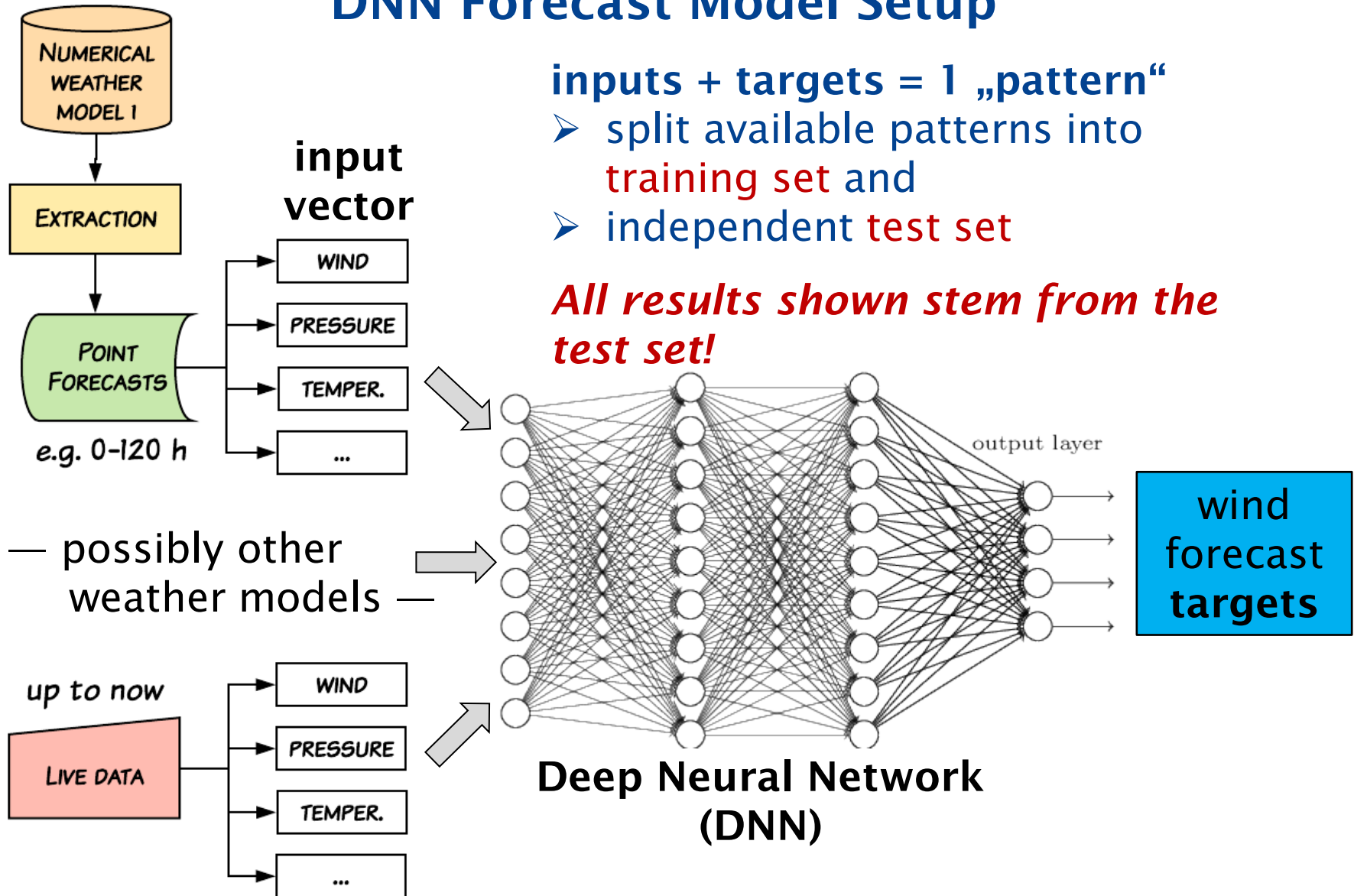
**Question: → How can uncertainty information be presented to DNNs?**

# DNN Forecast Model Setup

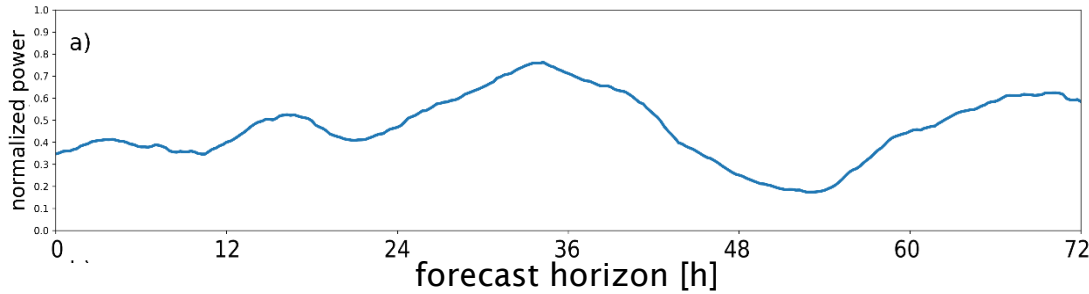
inputs + targets = 1 „pattern“

- split available patterns into training set and
- independent test set

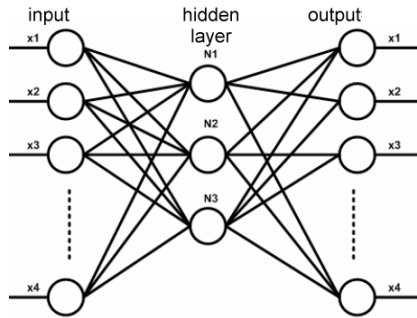
*All results shown stem from the test set!*



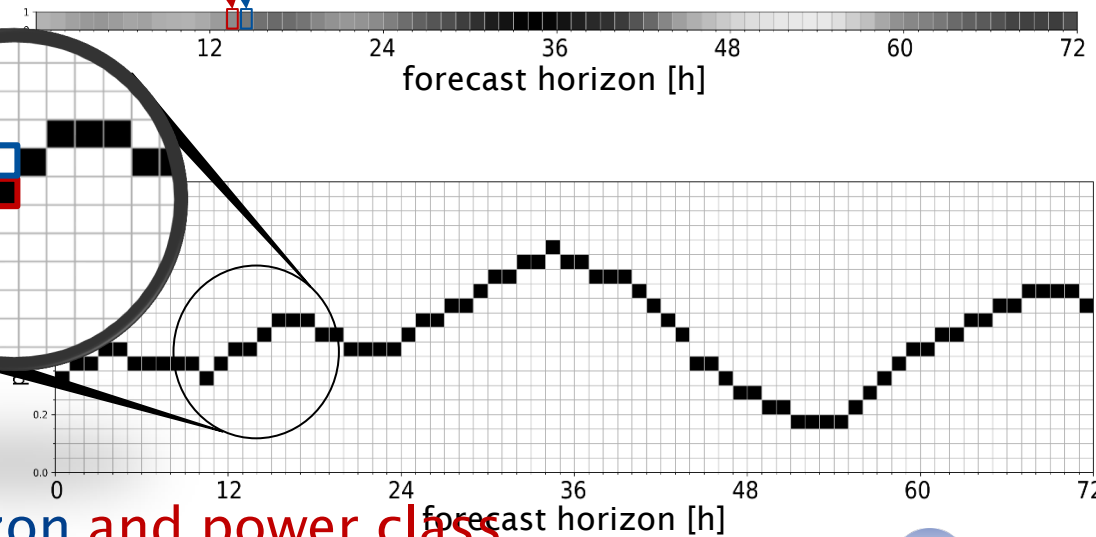
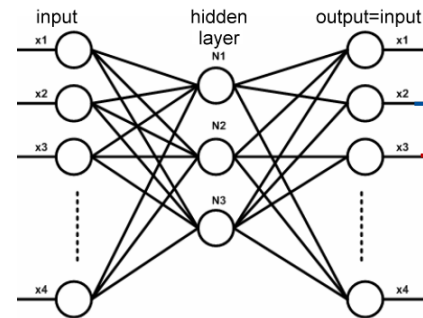
# Target Encoding



example targets:  
historical obs for one  
forecast run



traditional encoding:  
one neuron per forecast  
horizon



new encoding:  
one neuron per fc horizon and power class

# Input and Target Datasets

## Target data:

- Historical data from one wind farm in northern Germany
- EEX wind power data for Germany

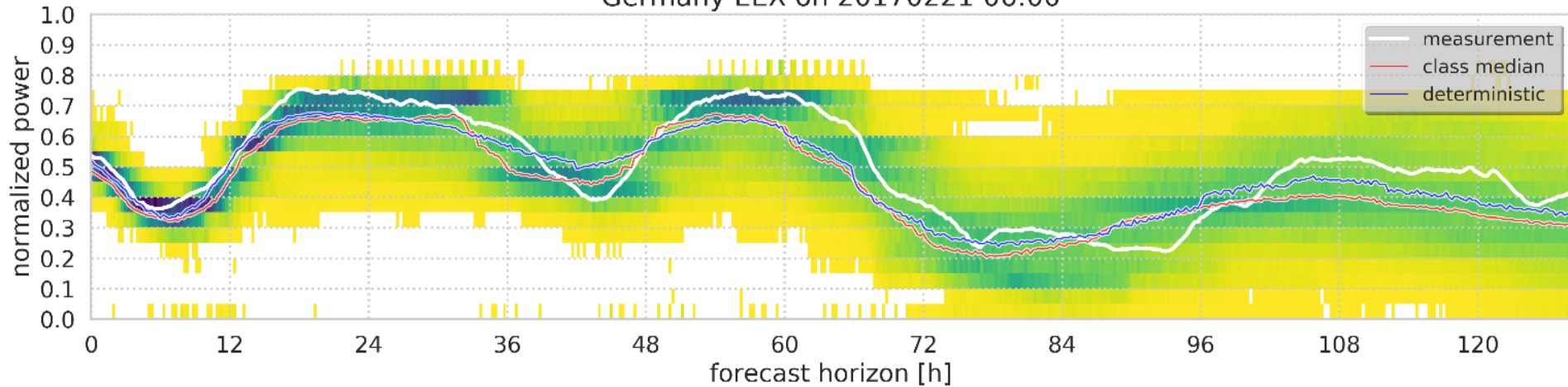
## Input data (=predictors):

- relevant fields from **GFS-4**, **IFS** and **HIRLAM** models
- live data (power measurements or EEX)

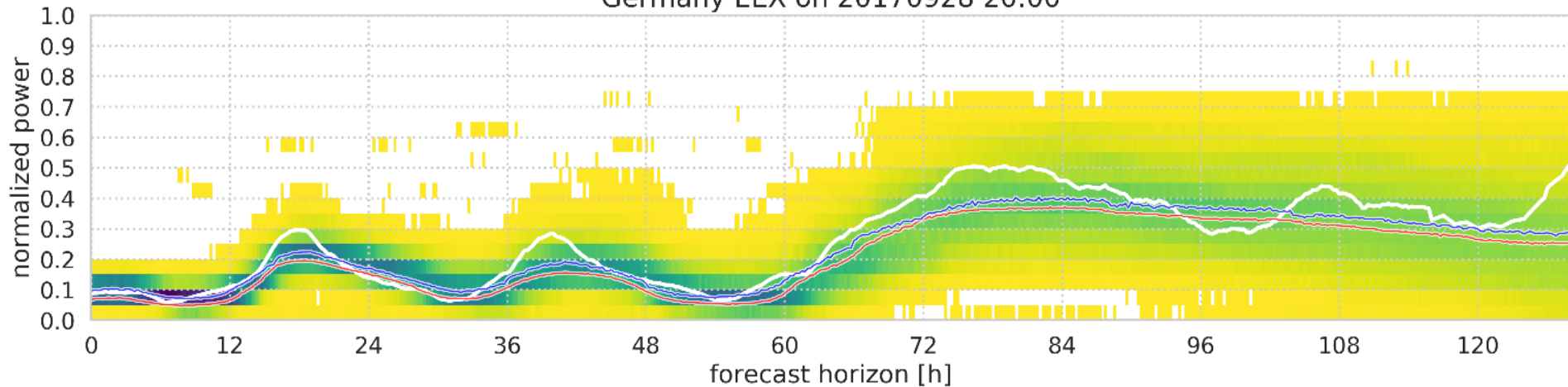
<b>Data set</b>	<b>Time range</b>	<b># of patterns</b>	<b>Test set</b>
Wind farm	2013–2017	~33000	12 months
EEX Germany	2015–2017	~26000	2017

# Probabilistic Forecast Results

Germany EEX on 20170221 06:00

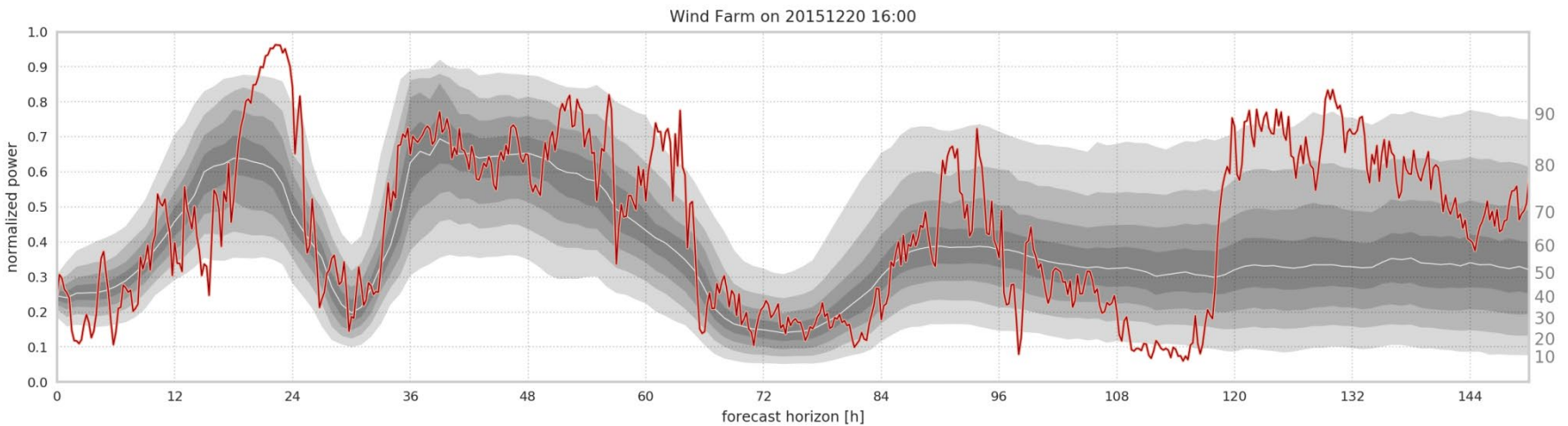
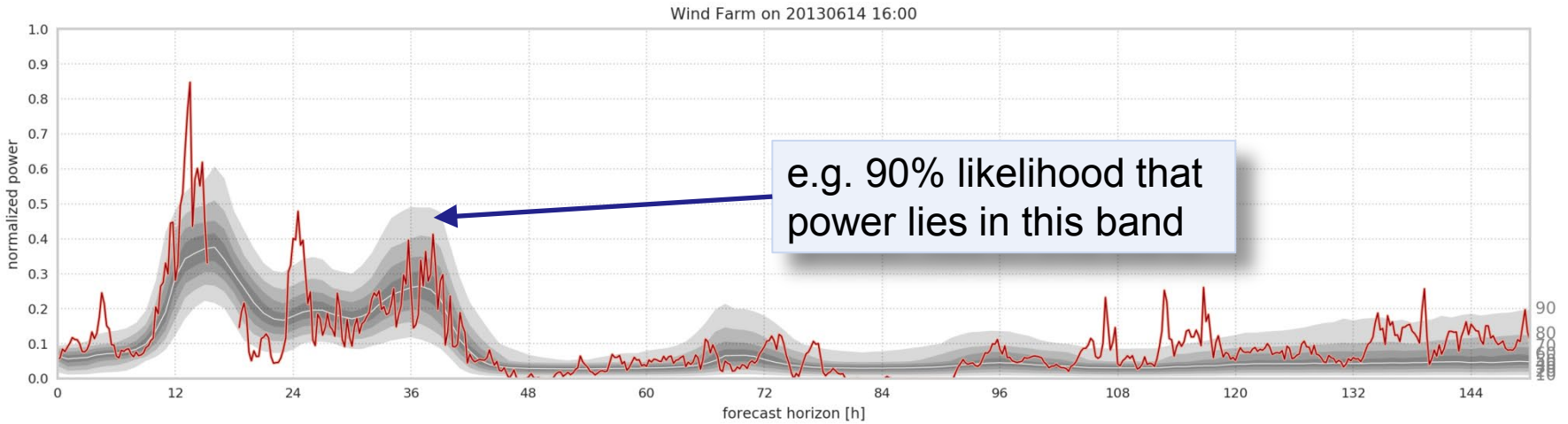


Germany EEX on 20170928 20:00



➤ shading corresponds to probability density

# Transforming into Percentiles



# Case Study for Wind Park in Chile

## Wind park Totoral:

- 23 Vestas V90 2MW
- Close to the Pacific coast

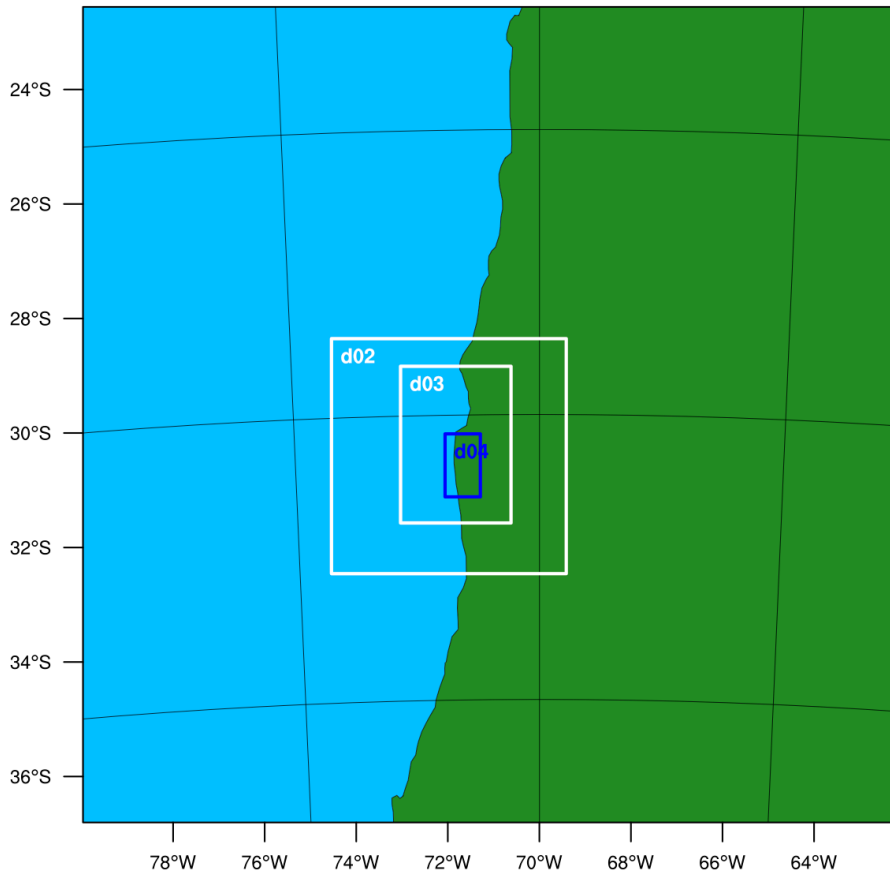
## Input data (=predictors):

- relevant fields from **GFS-4, Env. Canada, WRF** models
- live data (SCADA power measurements)

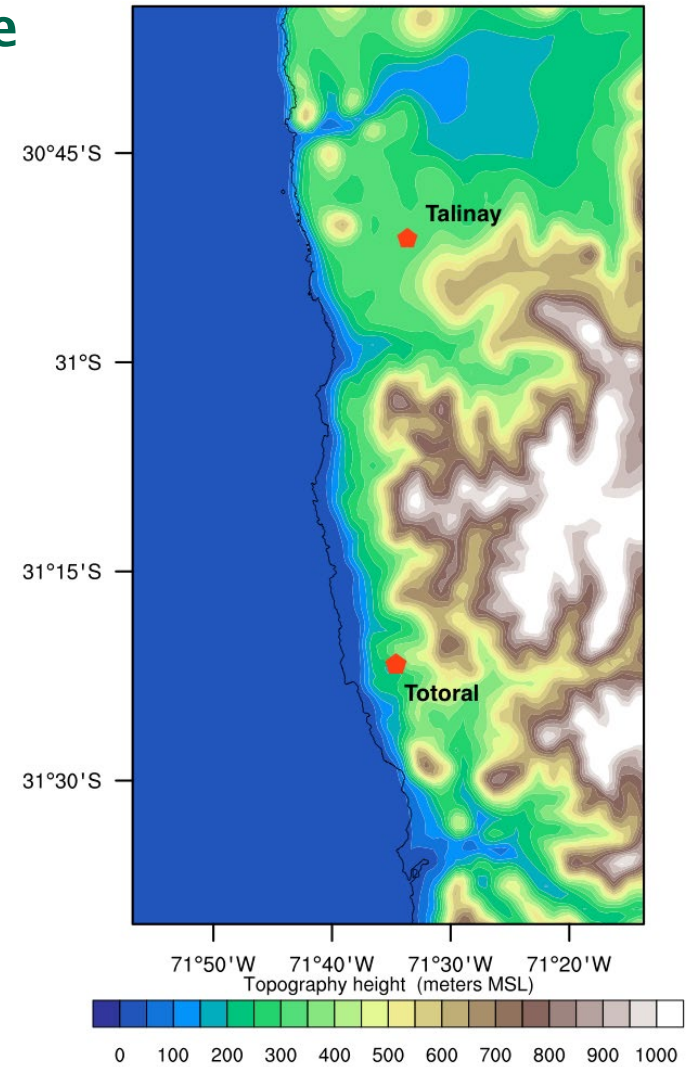


# Case Study for Wind Park in Chile

## Wind park Totoral: Local WRF mode

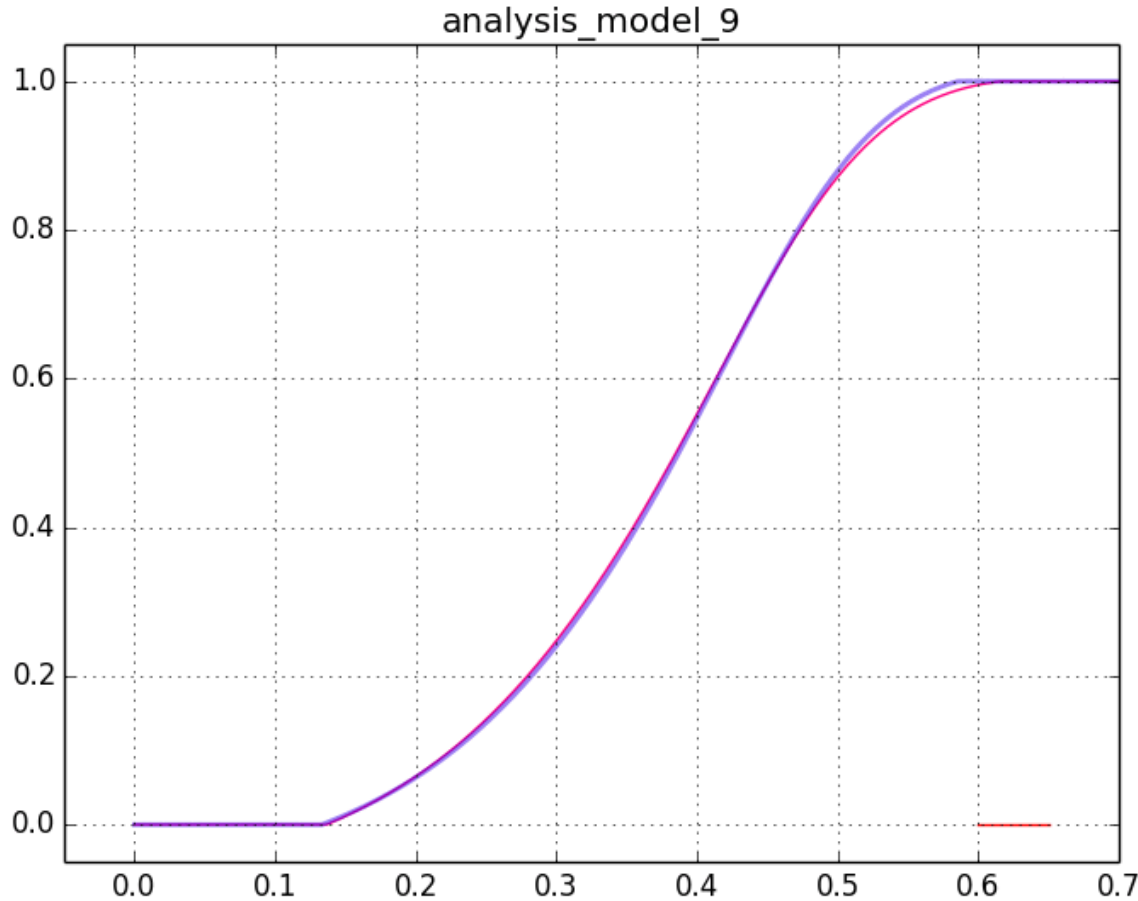


[source: Universidad de Valpariso]



# Case Study for Wind Park in Chile

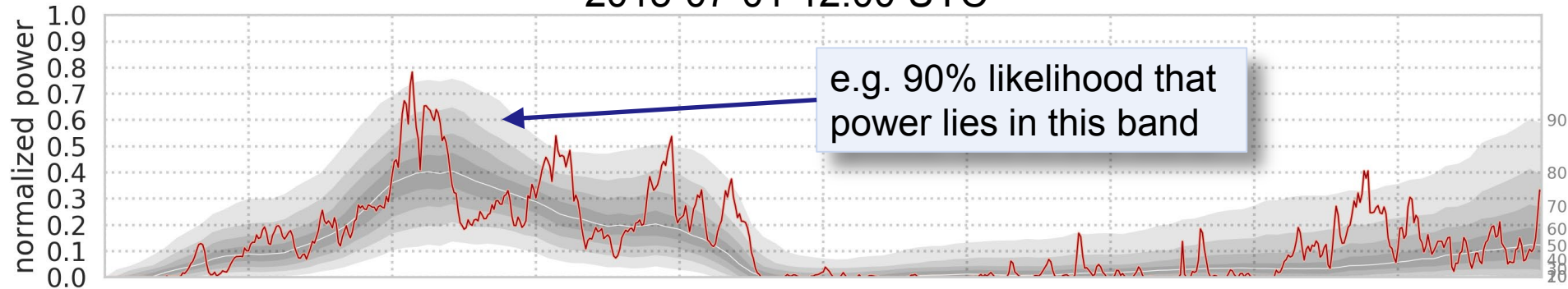
## Dependence of Power Curve from wind direction



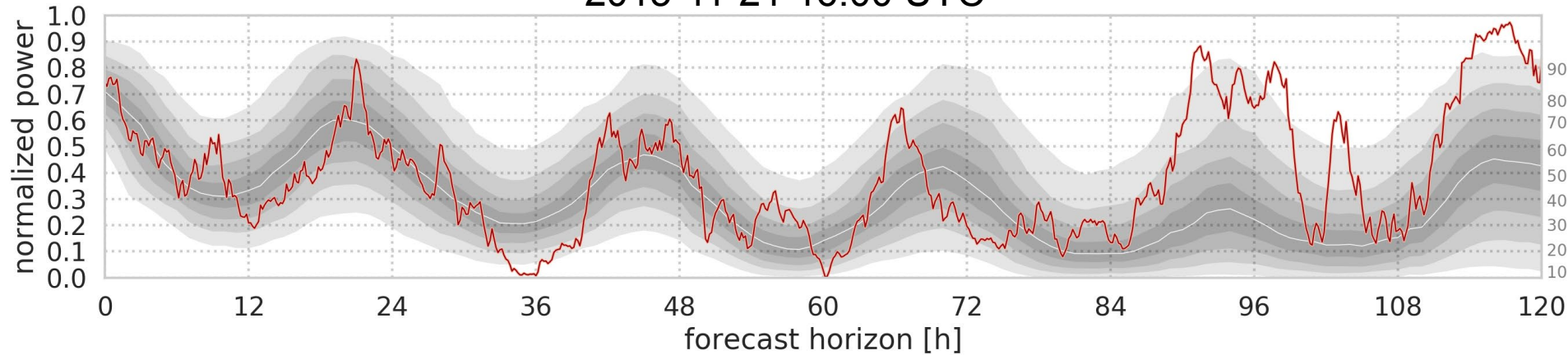
# Percentiles for Wind Park in Chile

Totoral Wind Park

2015-07-01 12:00 UTC

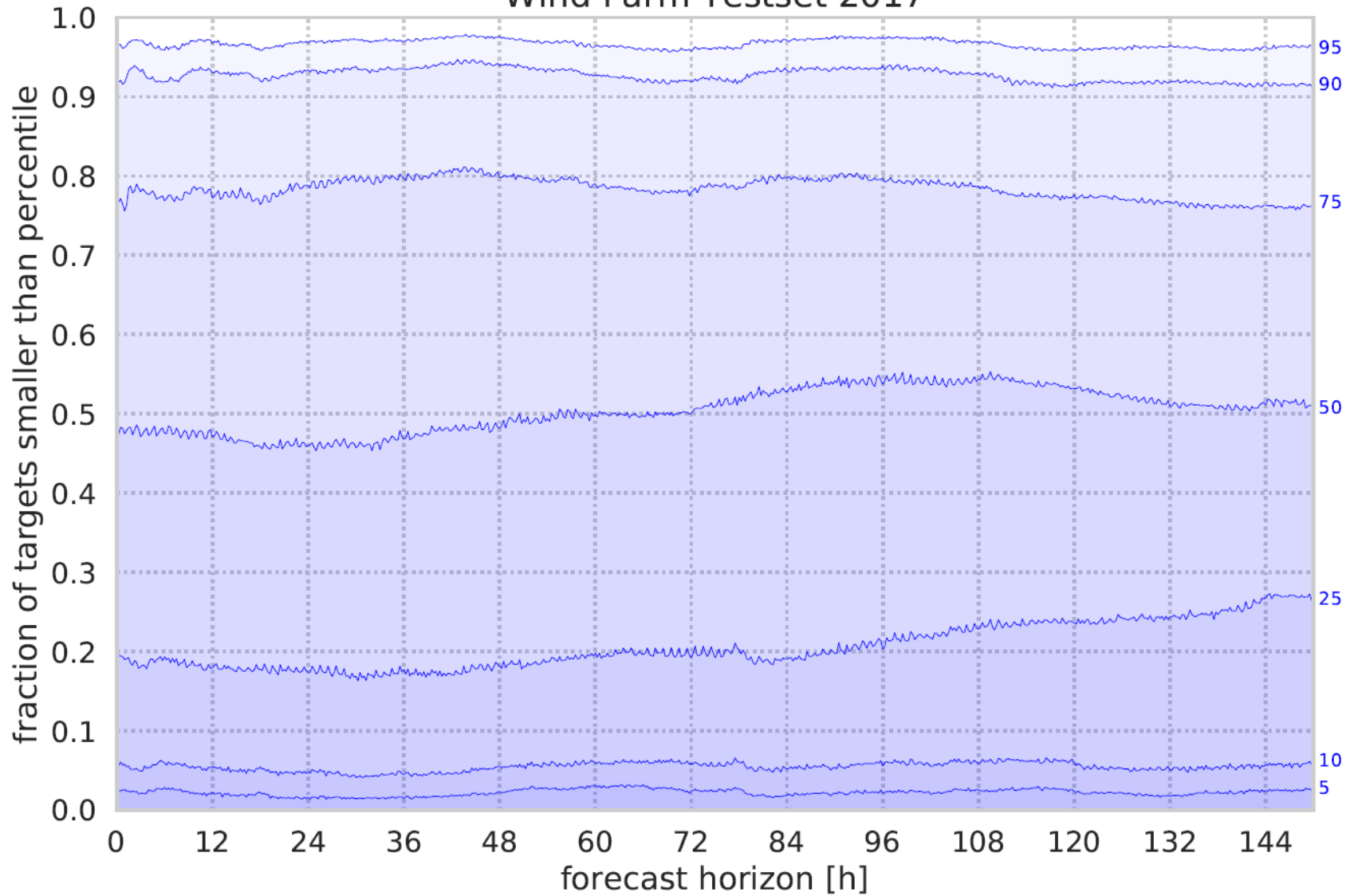


2015-11-21 16:00 UTC

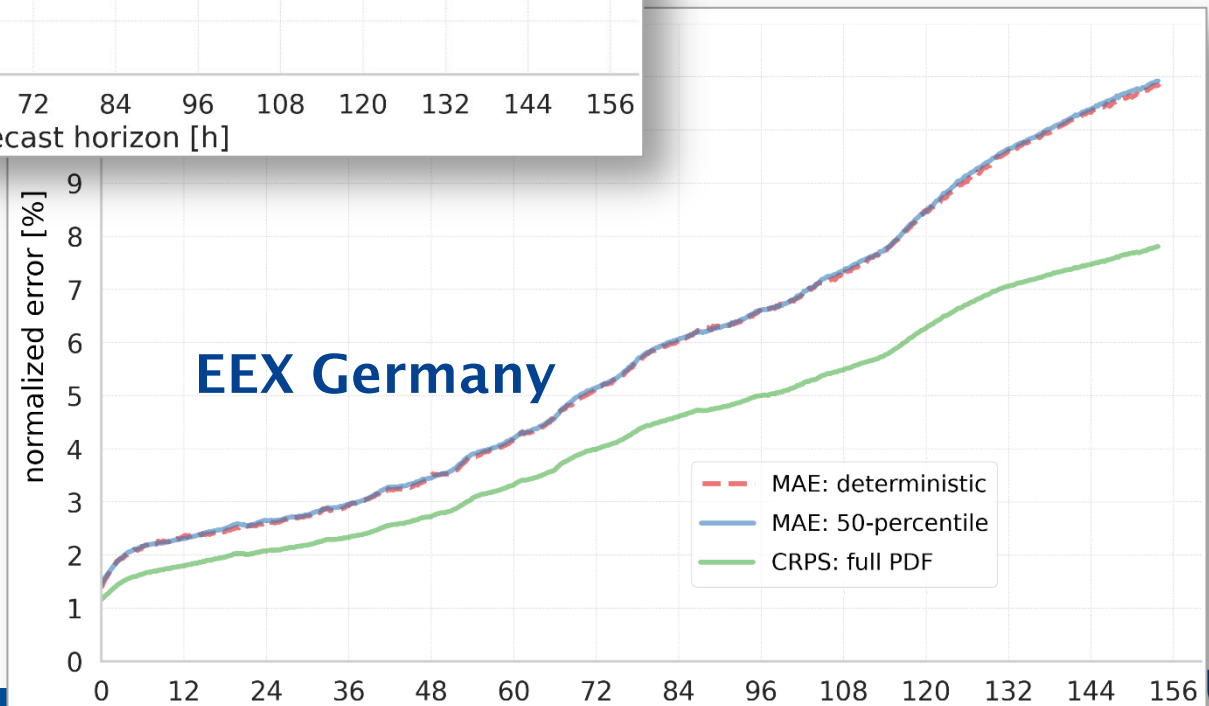
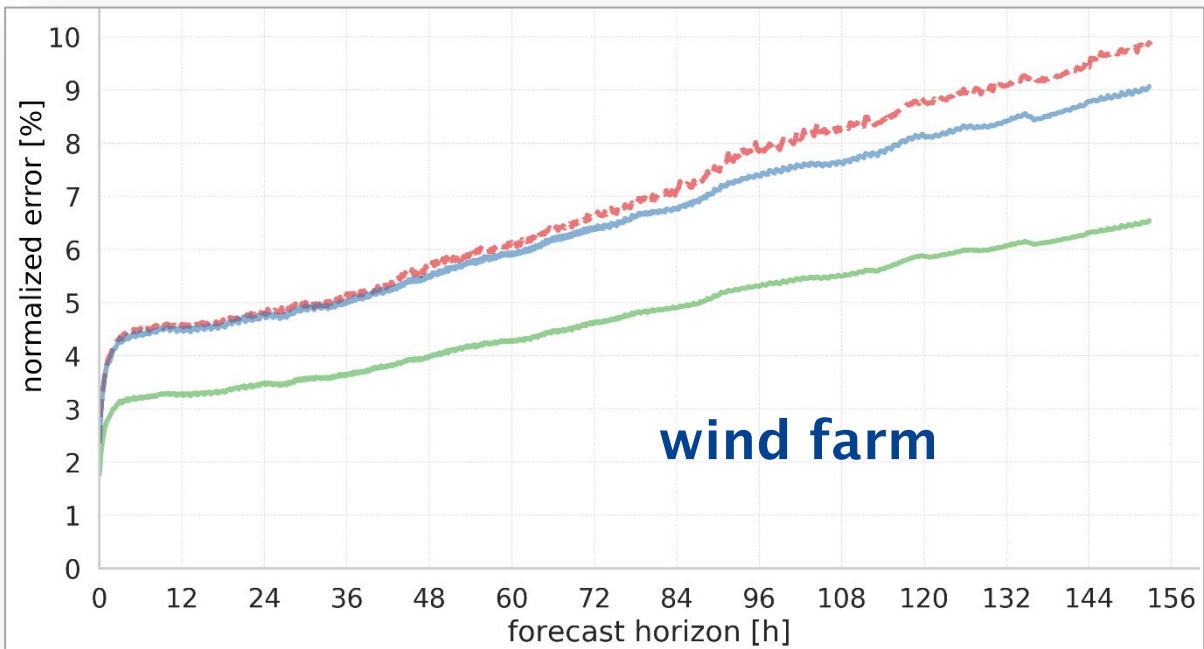


# Percentiles Validation

## Wind Farm Testset 2017



# Forecast Errors

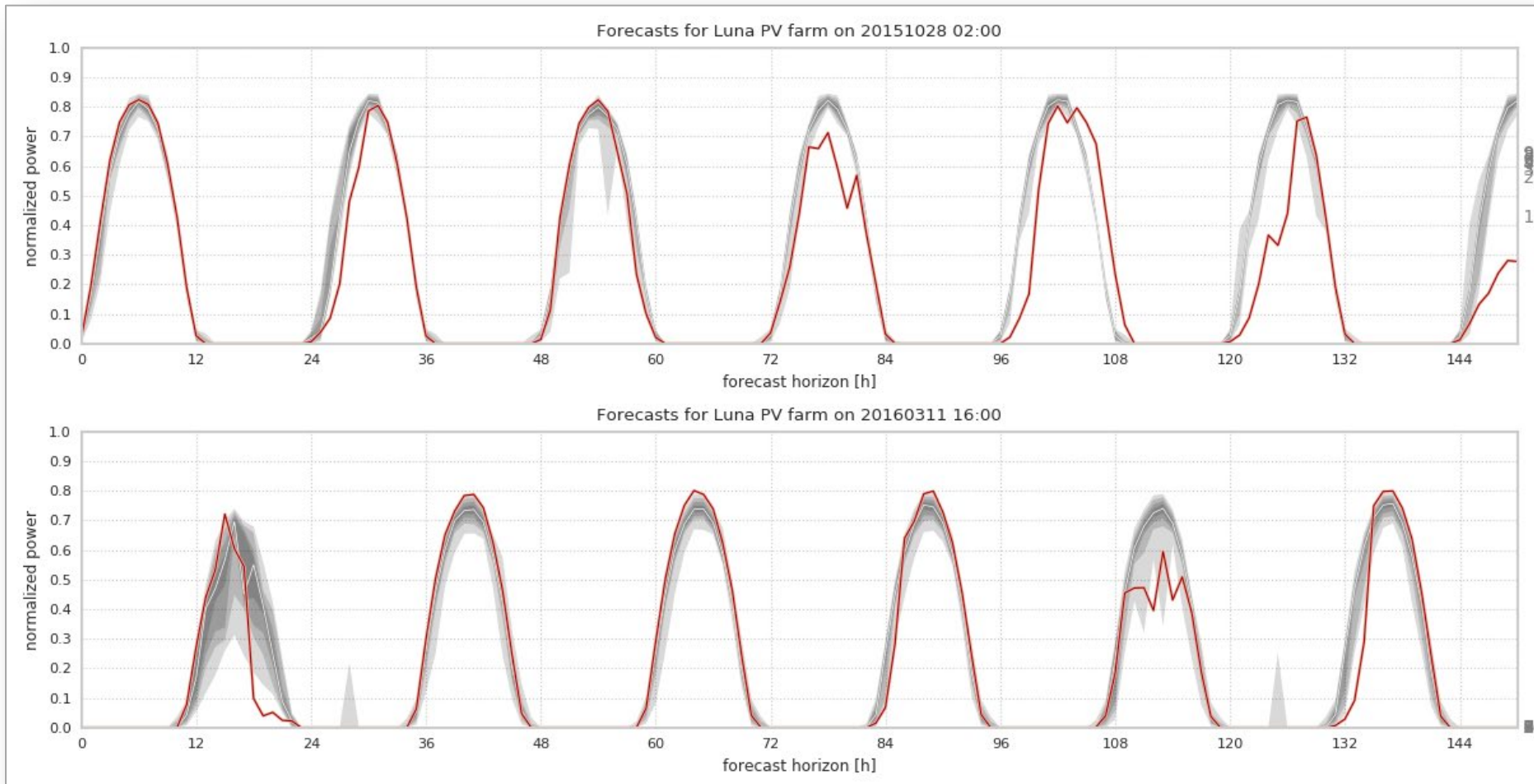


**CRPS:**  
Continuous Ranked Probability Score



# Same Story for PV Power Forecast

## Example: PV farm in Chile (1 h target resolution)



# Conclusions

- Simple method for producing **PDF forecasts** introduced
  - needs only discrete target encoding and some postprocessing
  - applicable for wind and PV power forecast
- Neural networks (DN) use **historical uncertainty** info
  - similar to Analog Ensemble method
  - plus uncertainty from (small) number of different NWP models
- Improved method in preparation for **operational application**



// Energy with a future

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# Thank you for your attention!

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