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Benchmark analysis of day-ahead solar power forecasting techniques using weather predictions

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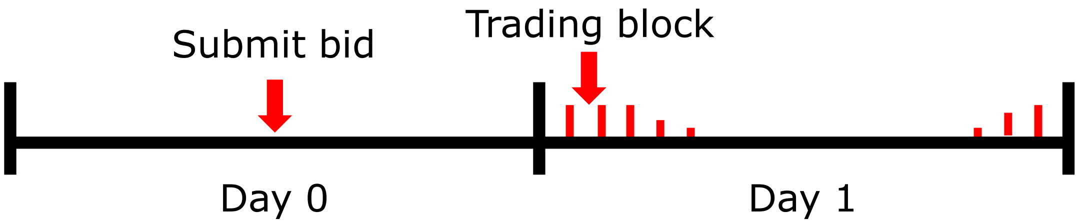
Introduction

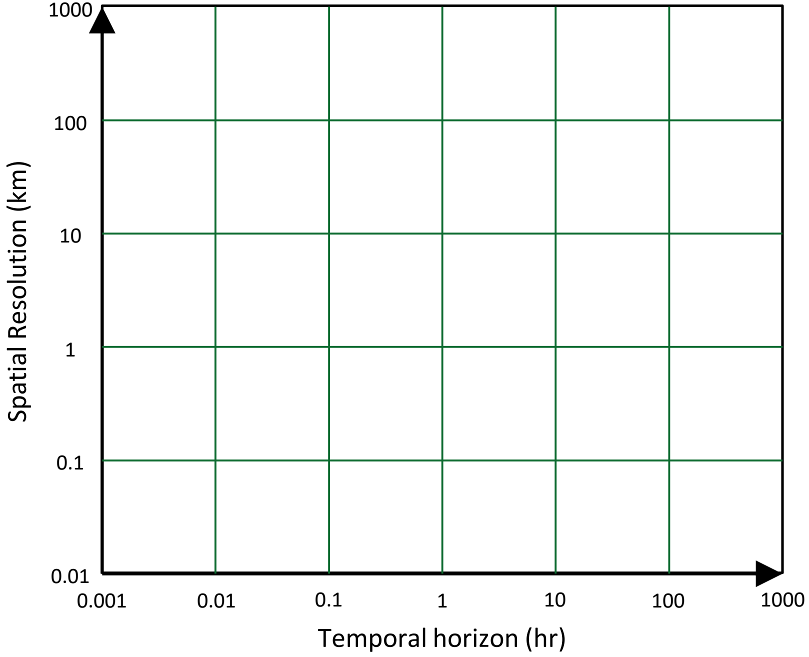
- Why day-ahead forecasting?
  - Most electricity traded in day-ahead market
  - Schedule dispatch of power generation

- Spot market trading:



- Lead time: 12 hours
- Horizon: 24 hours

Solar Forecasting Techniques



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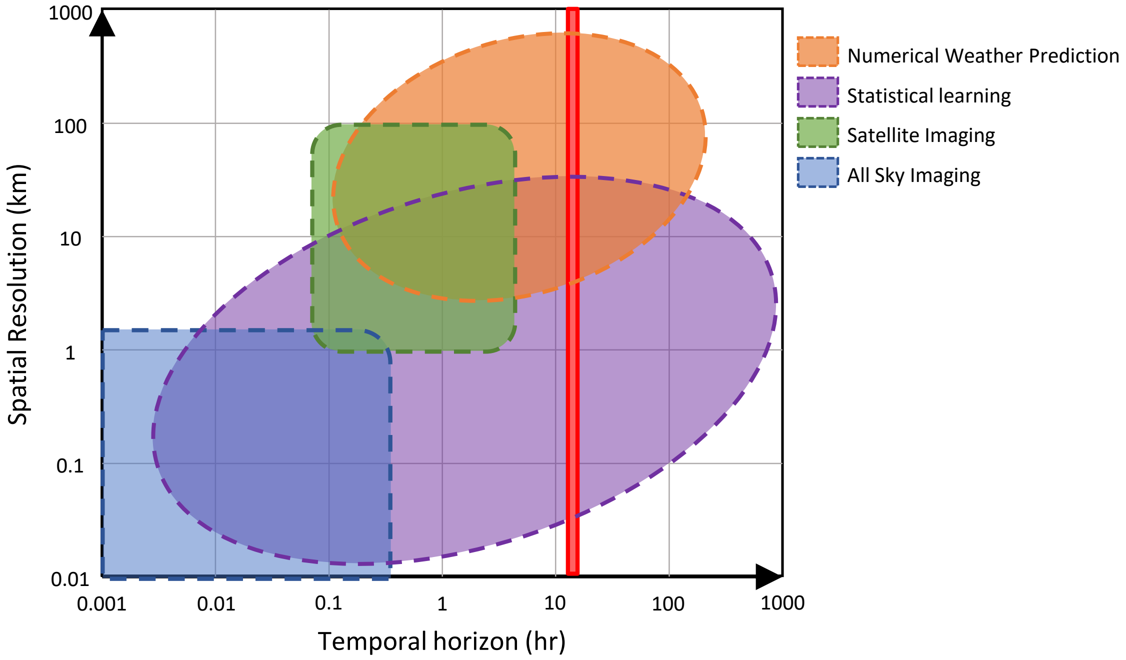
Solar Forecasting Techniques



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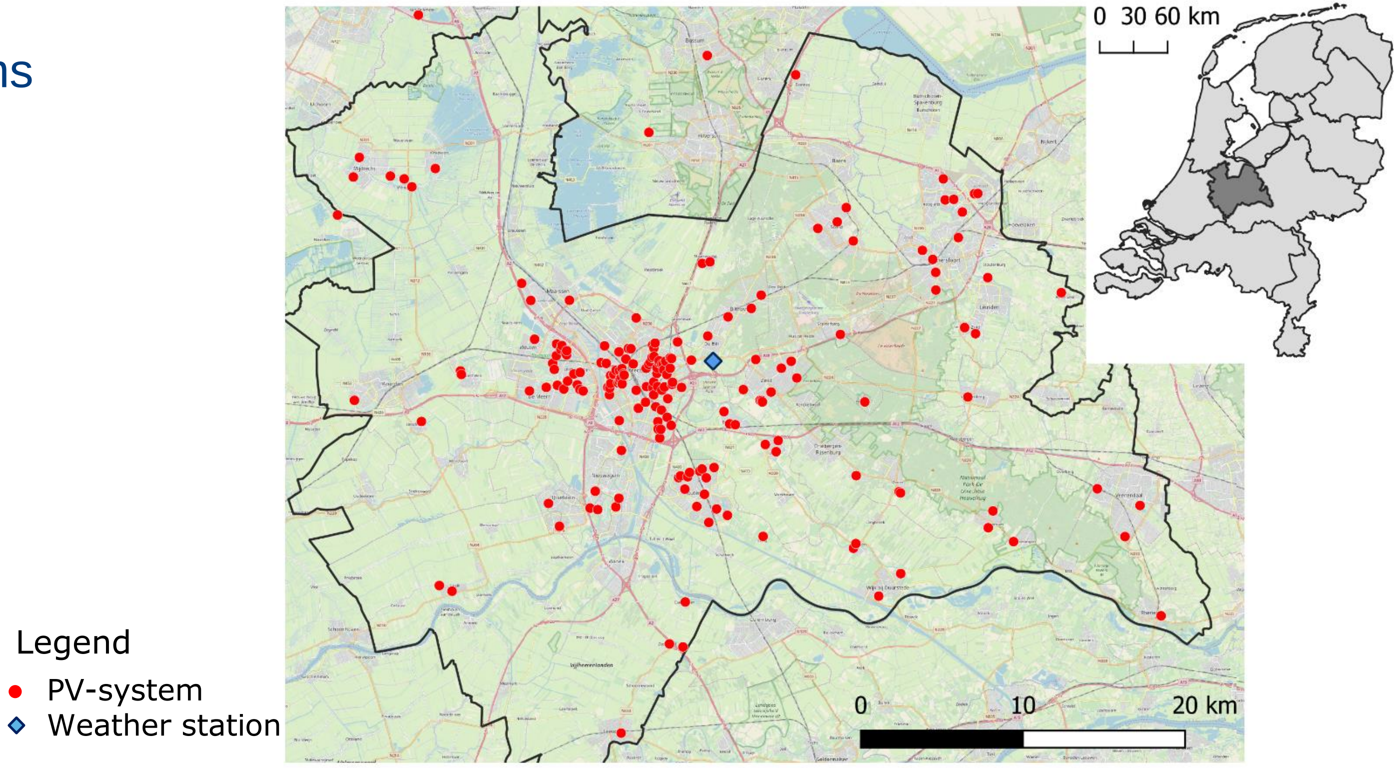
Contribution

- Comparison of models that utilize NWP to forecast the PV power output
- Examining the value of aggregating PV systems for forecasting

PV-systems in Utrecht

UPP-network

- 200 PV-systems
- Utrecht (NL)
- 38 x 54 km²
- 2013 - 2017



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Methods: Input Variables

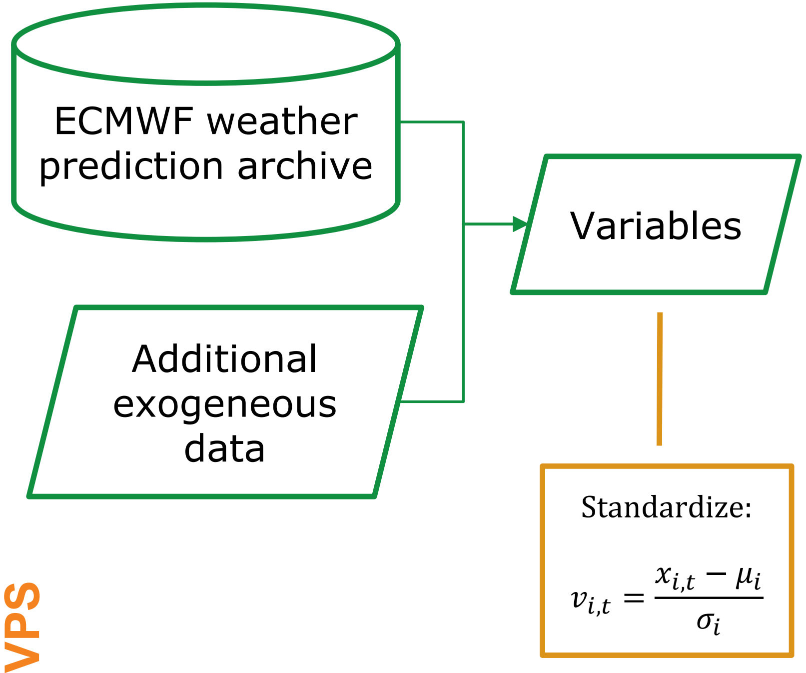
ECMWF weather prediction

- Mean sea level pressure
- Surface temperature at 2m
- Dewpoint temperature at 2m
- Zonal wind vector at 10m
- Meridional wind vector at 10m
- Surface solar radiation downwards
- Cloud cover at low, mid and high altitude
- Total precipitation

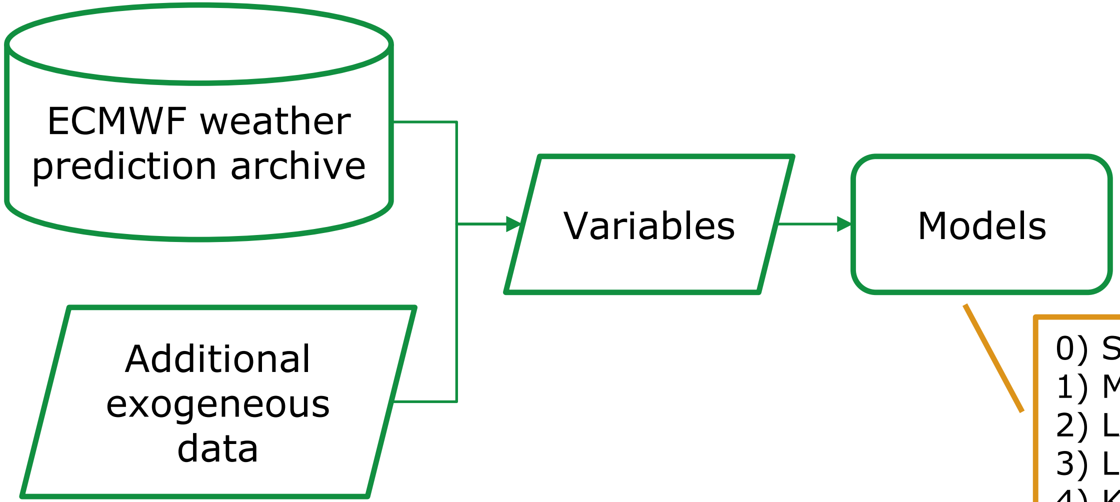
Additional exogeneous data

- Clear sky irradiance
- Solar zenith angle
- Month
- Hour

Methods: Process Variables



Methods: Forecasting Models



0) Smart Persistence (SP)
1) Multi-variate Linear Regression (MLR)
2) LASSO Regression (LASSO)
3) Linear Support Vector Machine (L-SVM)
4) Kernel Support Vector Machine (K-SVM)
5) Random Forests regression (RF)
6) Gradient Boosting regression (GB)
7) Feed-forward Neural Network (FNN)

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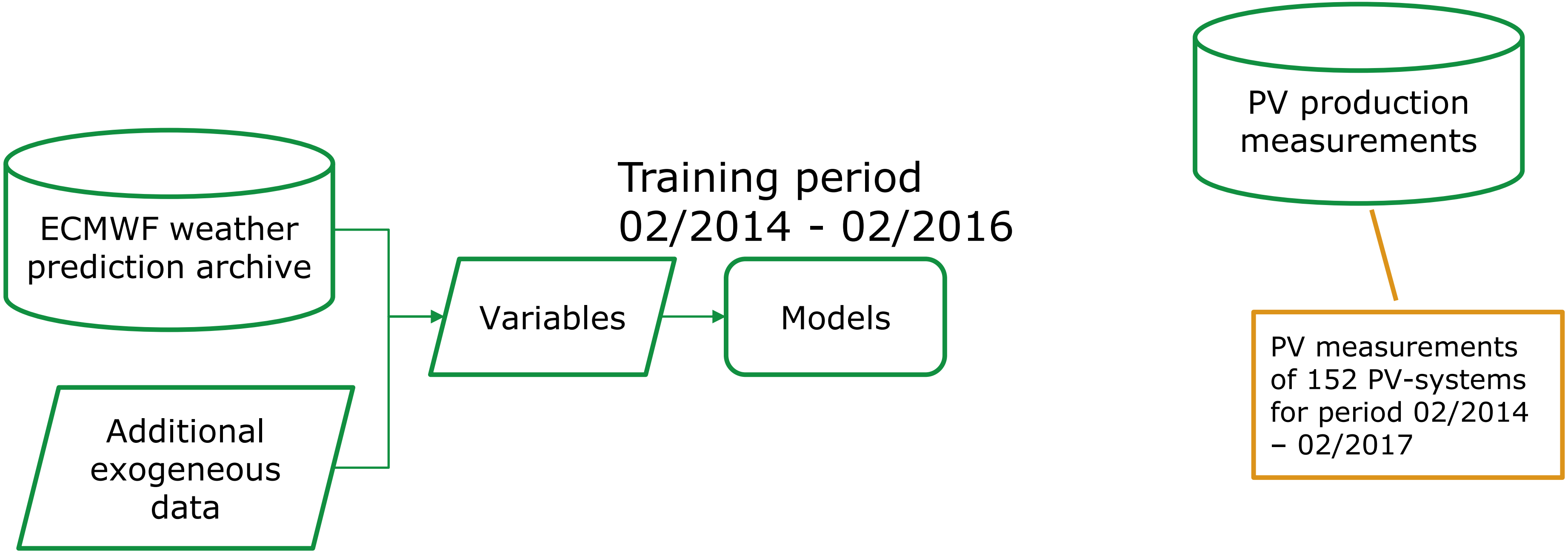
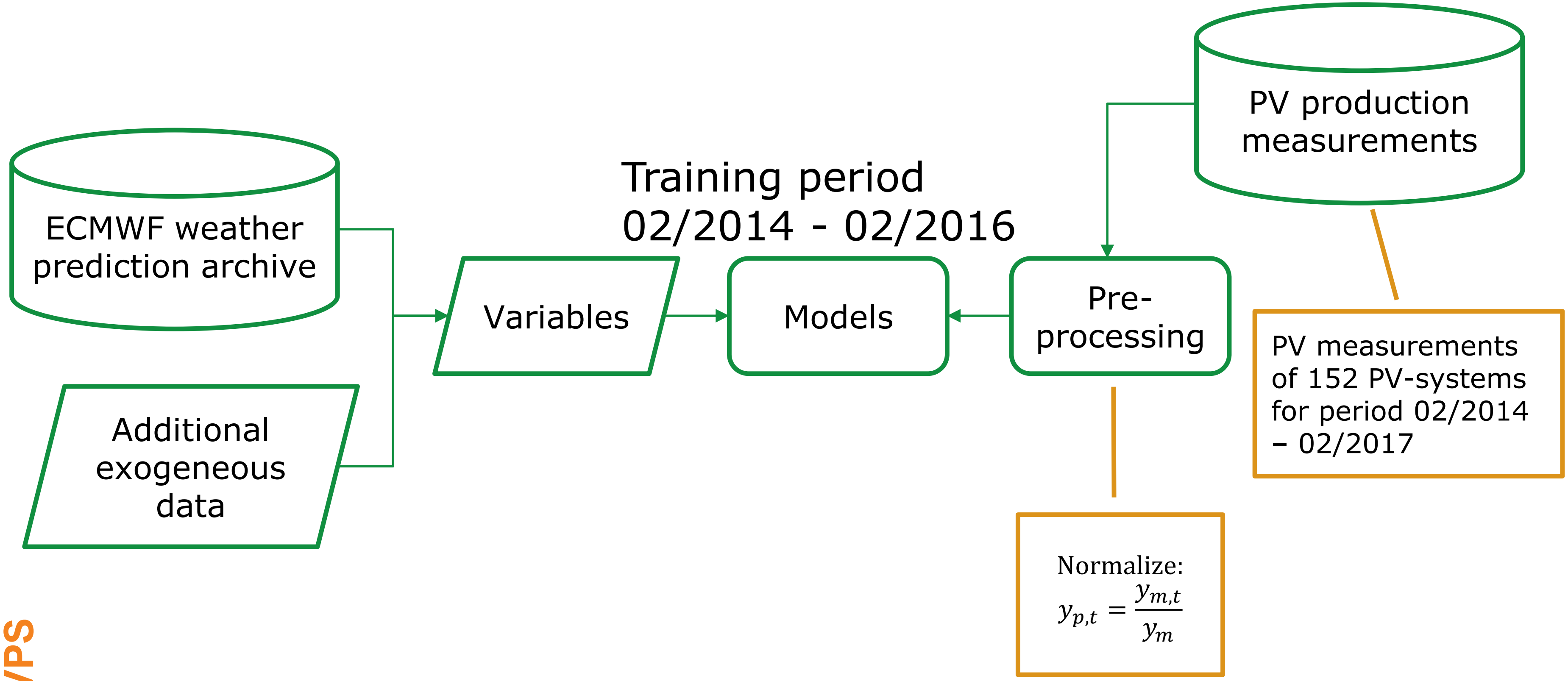
Methods: Train Models



Methods: Train Models



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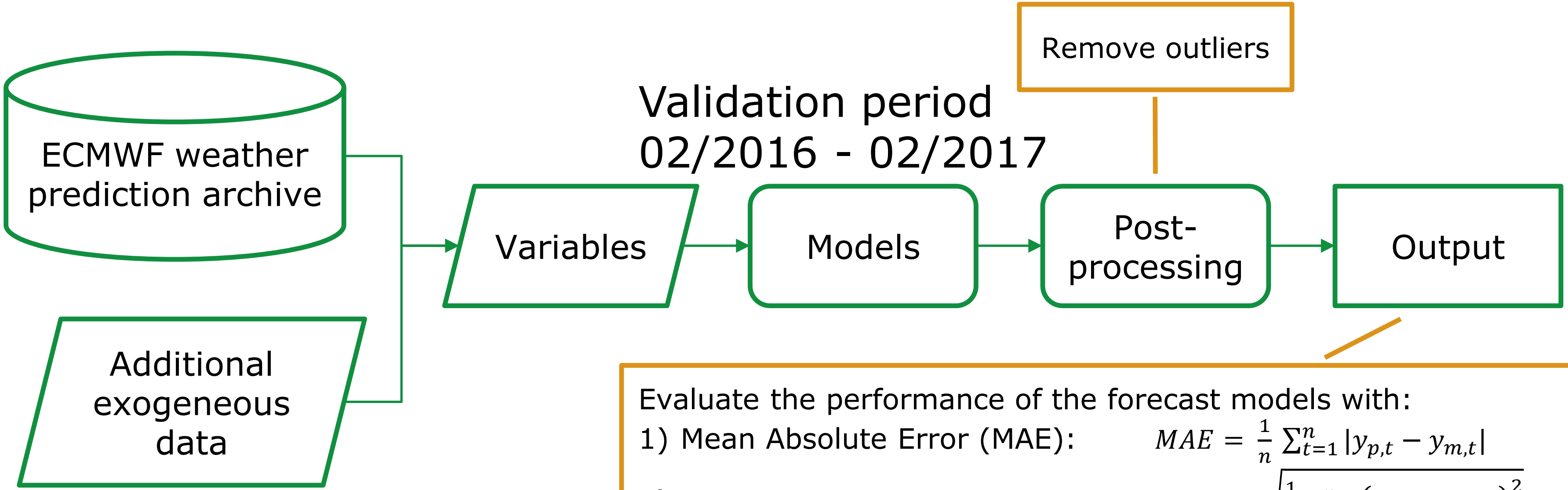
Methods: Forecast & Evaluation



Evaluate the performance of the forecast models with:

1) Mean Absolute Error (MAE): $MAE = \frac{1}{n}\sum_{t=1}^{n}|y_{p,t} - y_{m,t}|$

2) Root Mean Square Error: $RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_{p,t} - y_{m,t}\right)^2}$

3) Skill Score: $Skill\ Score = 1 - \frac{RMSE_{for}}{RMSE_{ref}}$

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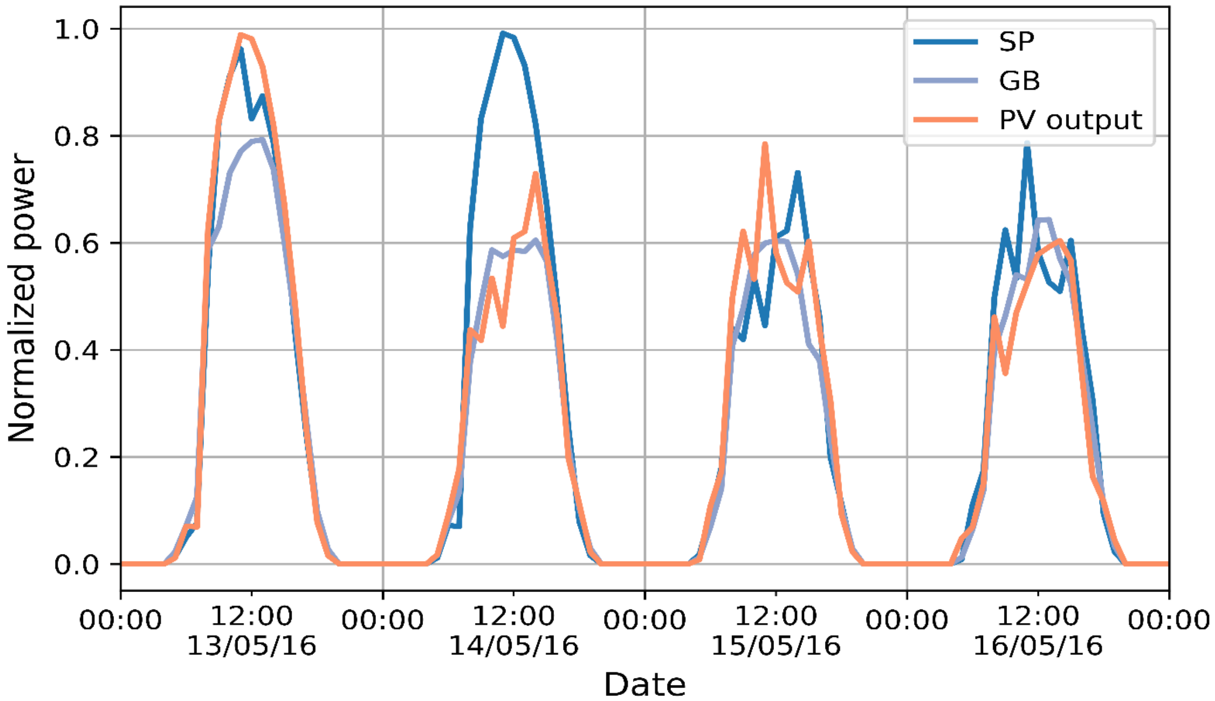
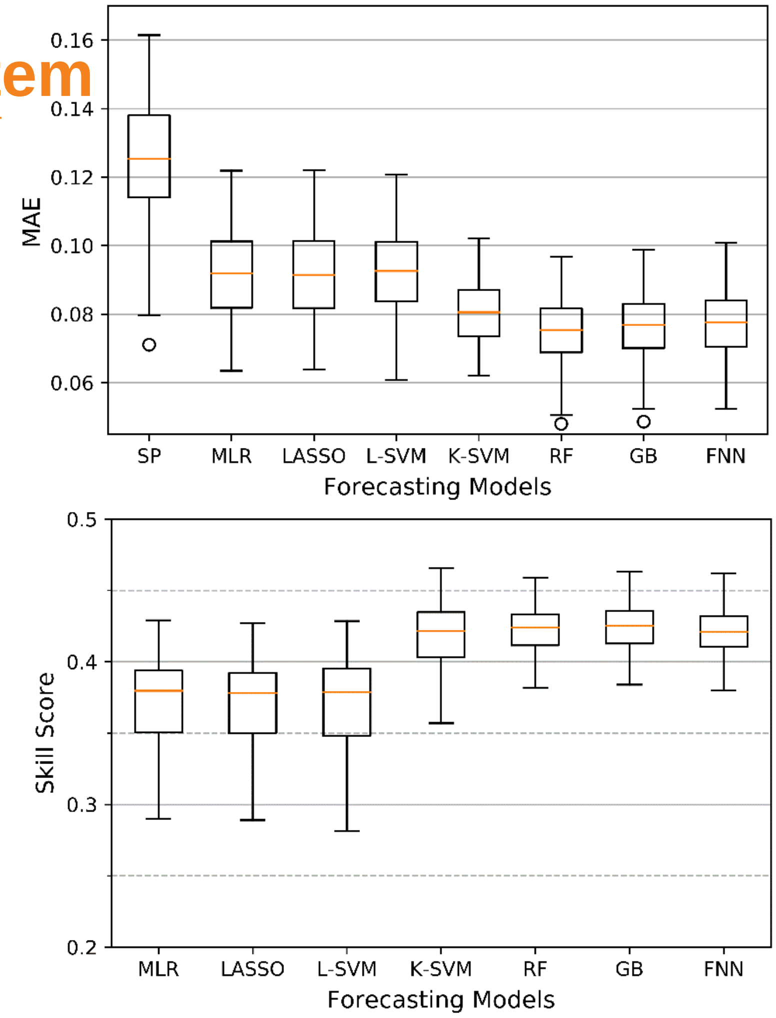
Results: Time-series Forecast

- Example of forecast



Results: Forecasting single PV-system

- All statistical models perform better than SP
- The more sophisticated statistical models outperform the linear models
- Best performance RF and GB



	K-SVM	RF	GB	FNN
MAE	8.04%	7.48%	7.63%	7.71%
Skill Score	40.1%	41.2%	41.4%	41.1%

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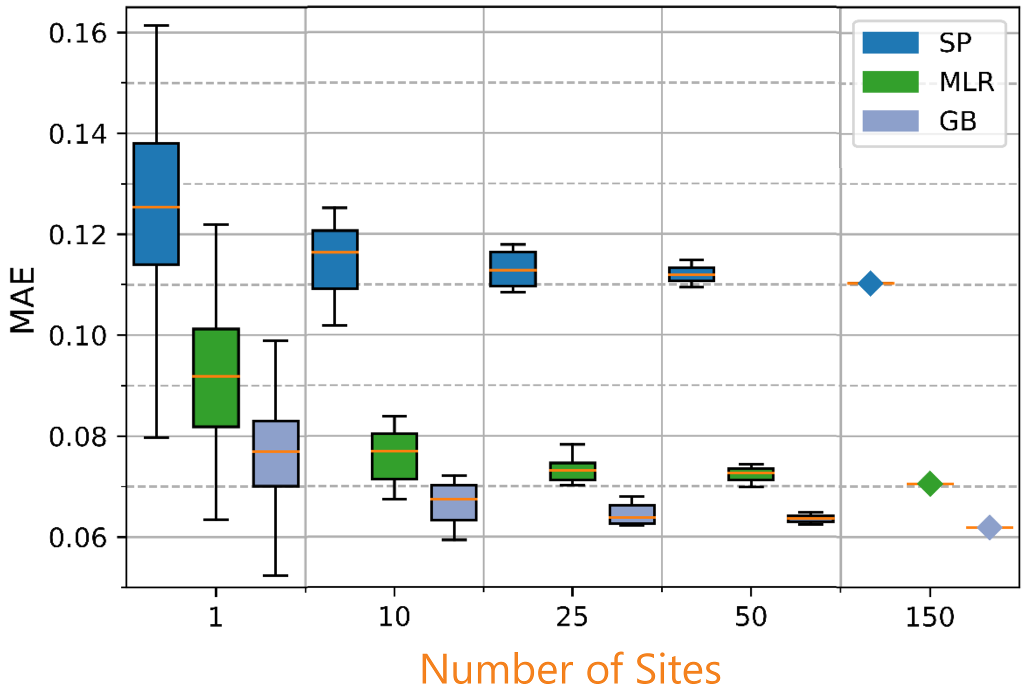
Results: Forecasting multiple PV-systems (1)

- The performance of all models improve as the number of sites increase:
  - Statistical models (20-25%)
  - SP (10%)
- The rate of improvement decrease as the number of sites increase
- Deviation of forecast errors decrease as the number of sites increase



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Forecasting multiple PV-systems

- All statistical models perform better than SP
- The more sophisticated models outperform the linear models
- RF best performance in terms of MAE
- K-SVM performs best in terms of the Skill Score

Models	MAE (%)	Skill Score (%)
SP	11.0	-
MLR	7.06	42.5
LASSO	7.06	42.0
L-SVM	7.20	42.5
K-SVM	6.29	46.5
RF	6.09	45.8
GB	6.19	45.9
FNN	6.30	46.1

MAE and Skill Score for 150 PV-systems

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Conclusions

- Comparison of statistical PV power forecasting models
- Single PV-system
  - Sophisticated models outperform the linear models
  - RF and GB outperform the other models
- Aggregated PV-systems
  - Benefits all forecasting models
  - Reduces the difference in errors among the statistical models

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