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# Short-term Solar Photovoltaic and Wind Power Generation Forecasts using Elastic Net in Time-Varying Forecast Combination

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# Agenda

- Research question and motivation
- Data and data pre-processing
- Methodology
- Empirical results
- Conclusions

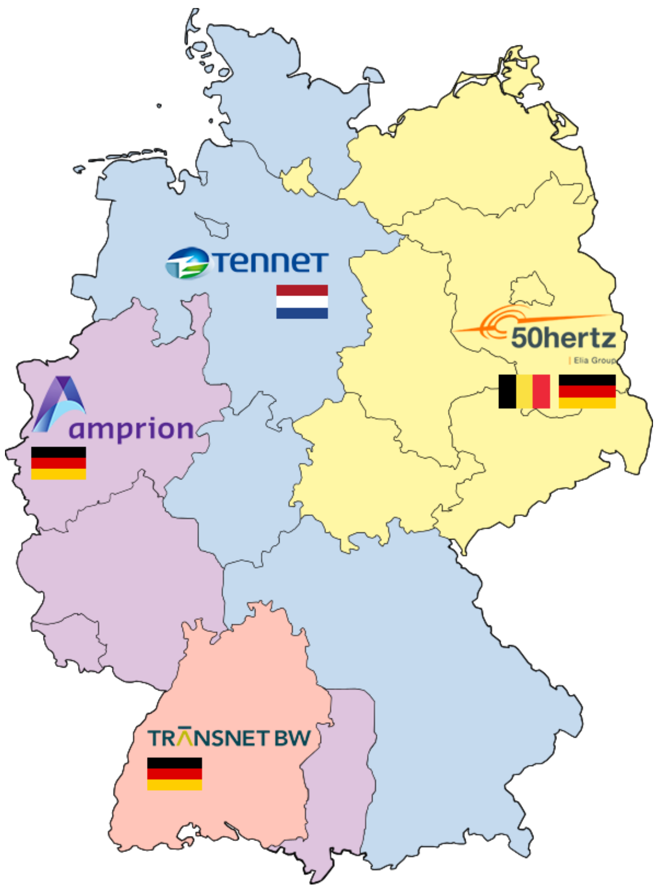
# Forecast combinations in the field of renewable energy

- Forecast solar photovoltaic (PV) and wind feed-in, with low forecasting errors
- Elastic Net methodology for obtaining forecast combinations for PV and wind data
  - meta-forecasts proven to be superior to individual forecasts
  - takles the issue of multicollinearity between individual forecasts
- Whether such combined day-ahead forecasts of PV and wind feed-in outperform:
  - individual forecasts
  - benchmarks such as the simple average (SA)

# Motivation

- Net electricity generation from renewable energy sources (RES) in Germany has increased from 19.2 % in 2010 to 46 % in 2019
- Precise RES feed-in forecasts aim to reduce the uncertainty related to these variable energy sources and to ensure system stability, especially with increasing installed capacity of RES
- RES feed-in forecasts are used by:
  - PV and wind plant operators (to minimize deviation between forecasted and produced energy)
  - System operators (to determine the reserve requirements and to manage their balancing groups)
  - Traders (to optimize their trading activities)

# Data-PV / Wind




- obtained in cooperation with 50Hertz, one of Germany’s TSOs
- approximately 25 % / 32 % of total installed PV / wind capacity in Germany
- covers the period 2012–2018 for PV / 2010–2018 for wind
- data is gathered in quarter-hourly intervals, totaling 245,472 / 315,552 realizations of PV / wind feed-in (in MW)
- day-ahead PV / wind forecasts (at 9 a.m.) for feed-in as provided by the six / seven different forecasts providers (F1–F6 / F7) as well as a combined forecast by 50Hertz (K)

# PV data structure



| | $HR^{PV}$ | $K^{PV}$ | $F1^{PV}$ | $F2^{PV}$ | $F3^{PV}$ | $F4^{PV}$ | $F5^{PV}$ | $F6^{PV}$ |
|---|---|---|---|---|---|---|---|---|
| 2012 | | from 03.08. | | | | | | |
| 2013 | | | | | | | | |
| 2014 | | | | | from 15.02. | | from 01.06. | |
| 2015 | | | | | | from 07.05. | | |
| 2016 | | | | | | | | |
| 2017 | | until 12.05. | until 03.03. | | until 20.07. | until 14.06. | | |
| 2018 | | | | | | | | |

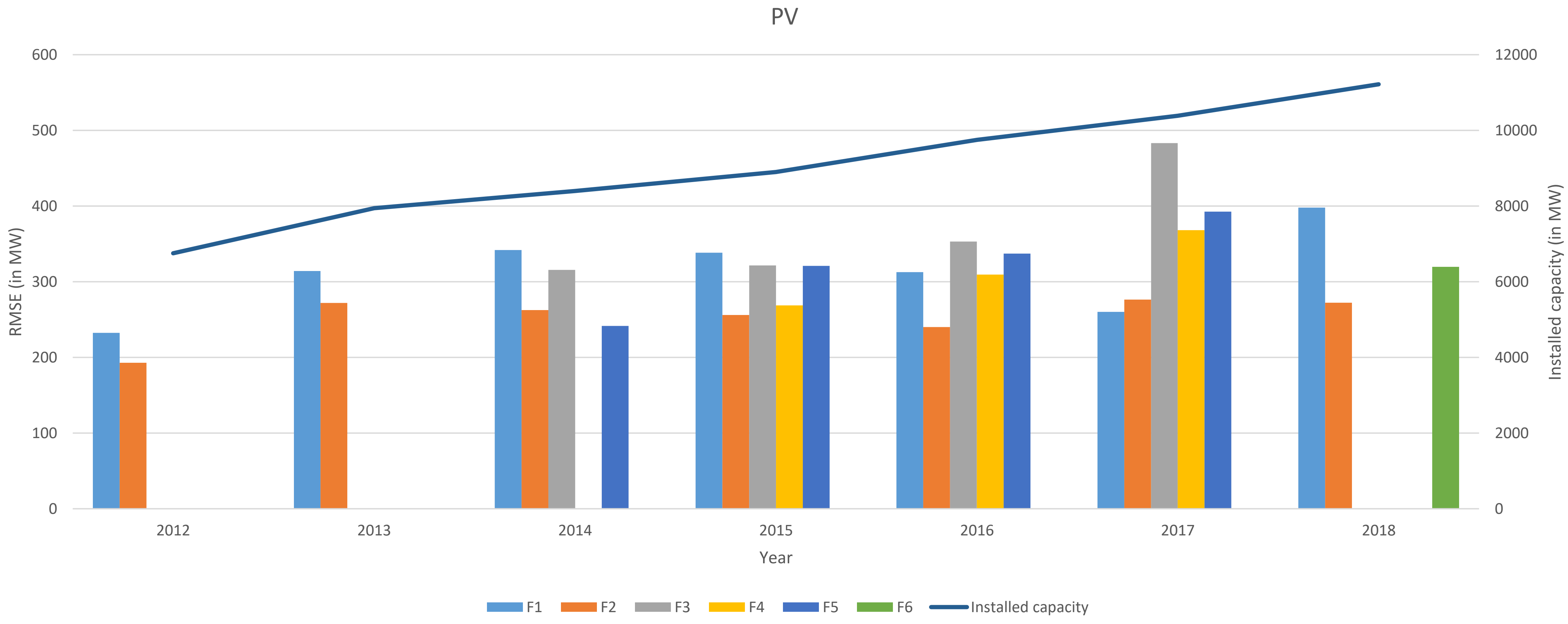
- $HR^{PV}$ is the realization of photovoltaic feed-in
- $K^{PV}$ is the combined forecast by 50Hertz
- $F1^{PV}$–$F6^{PV}$ include the day-ahead PV forecasts as provided by the six different forecasts providers
- Dark blue - data is complete for the whole year; light blue - the data is only partially available

# Wind data structure

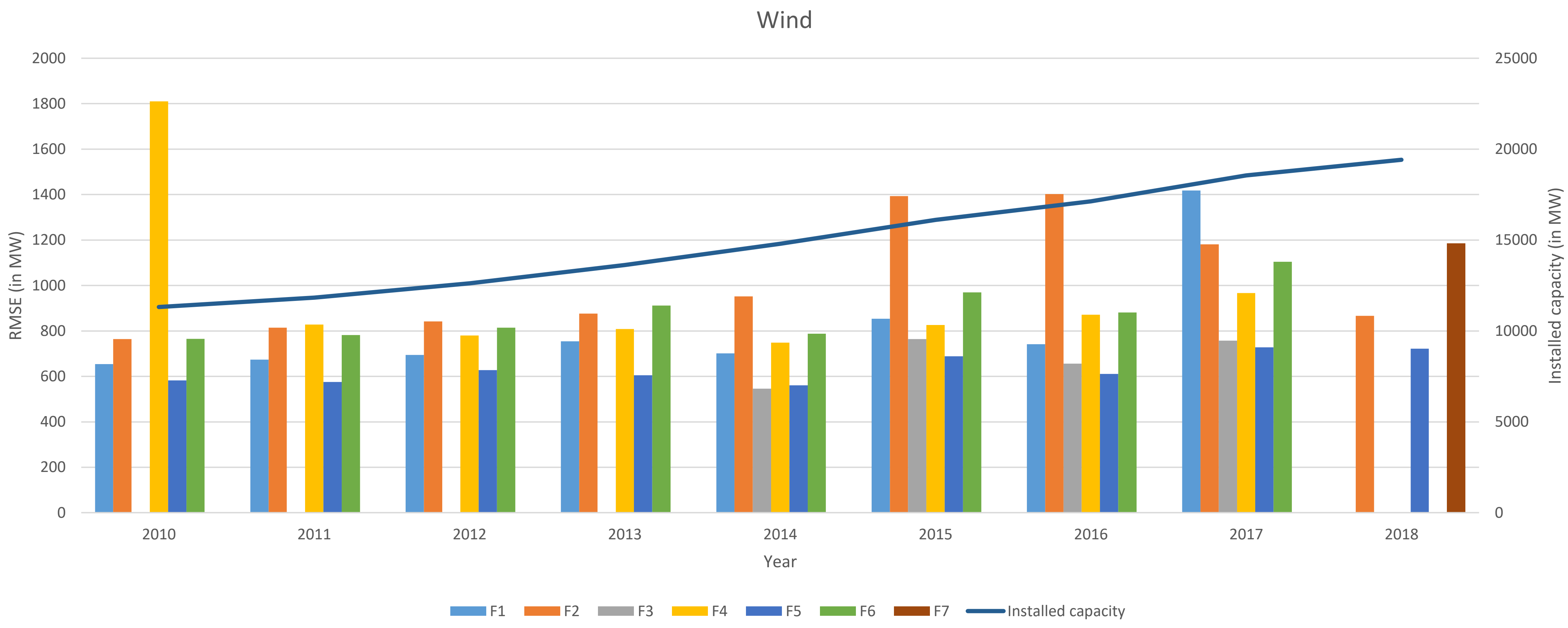
| | Wind | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $HR^{wind}$ | $K^{wind}$ | $F1^{wind}$ | $F2^{wind}$ | $F3^{wind}$ | $F4^{wind}$ | $F5^{wind}$ | $F6^{wind}$ | $F7^{wind}$ |
| 2010 | | | | | | | | from 26.06. | |
| 2011 | | | | | | | | | |
| 2012 | | | | | | | | | |
| 2013 | | | | | | | | | |
| 2014 | | | | | from 10.10. | | | | |
| 2015 | | | | | | | | | |
| 2016 | | | | | | | | | |
| 2017 | | | until 17.05. | | | until 17.05. | | until 26.01. | |
| 2018 | | | | | until 05.01. | | | | |

- $HR^{wind}$ is the realization of wind feed-in
- $K^{wind}$ is the combined forecast by 50Hertz
- $F1^{wind}$–$F7^{wind}$ include the day-ahead wind forecasts as provided by the seven different forecasts providers
- Dark blue - data is complete for the whole year; light blue - the data is only partially available

# Precision of the individual PV forecasts



# Precision of the individual wind forecasts



# Dynamic data pre-processing (DDP)

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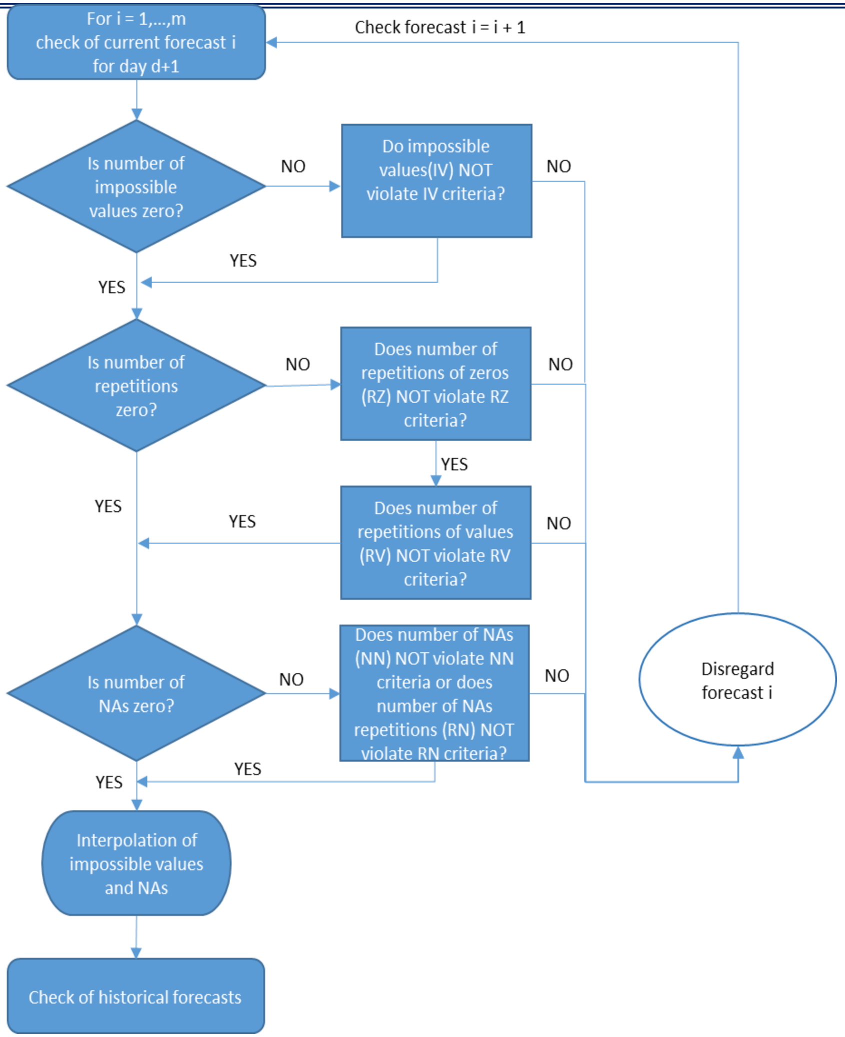
Pre-processing of day ahead forecasts 96 values (Step 1) //

historical forecasts data - past 15,780 observations (Step 2)

- Impossible values
  - Smaller than 0 or larger than installed capacity (max. 5 // 100)
- Values repetitions
  - 0s (max. 68 // 960)
  - Repetitions of non-zero values (max. 10 // 960)
- Missing values
  - Total (max. 10 // 960)
  - Following one another (max. 5 // 96)



# Elastic Net Model (type of regularization)



- with highly correlated predictors, one important task is to decrease the model's complexity (deliver a parsimonious model) and to reduce multi-collinearity
  - regularization (or shrinkage): the process of shrinking estimated coefficients, leading to lower variance of the coefficients
  - the process is beneficial for the model's predictive performance as shrinkage reduces the forecasting errors
- special form of regression
- trade-off between the „Ridge“- and the „LASSO“- regressions
- prevents over-fitting

# Elastic Net objective function

$$\min_{(\beta_{0,t'},\boldsymbol{\beta}_{t'})} \frac{1}{2N} \sum_{t=t'-N+1}^{t'} \left(\varphi_t - \beta_{0,t'} - \tilde{\boldsymbol{\varphi}}_t^T \boldsymbol{\beta}_{t'}\right)^2 + \lambda[\alpha \|\boldsymbol{\beta}_{t'}\|_1 + (1-\alpha)\|\boldsymbol{\beta}_{t'}\|_2^2/2] \, , \qquad (1)$$

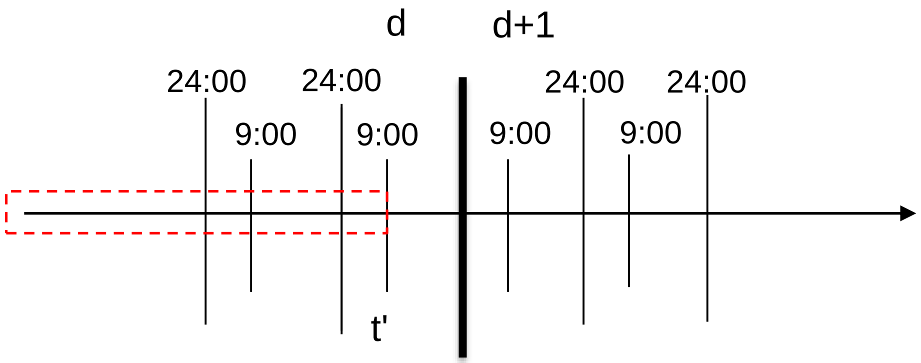
- $\beta_{0,t'}^*$ and $\boldsymbol{\beta}_{t'}^* = \left(\beta_{1,t'}^*, \ldots, \beta_{m,t'}^*\right)^T$ - the optimal model coefficients;
- $\tilde{\boldsymbol{\varphi}}_t^T = (\tilde{\varphi}_{1t}, \ldots, \tilde{\varphi}_{mt})^T$ - includes the $m$ different individual forecasts for each $t$ from the historical time frame: $[t' - N + 1, t']$ ;
- $\varphi_t$ - the associated realizations of PV and wind power;
- $(\lambda \|\boldsymbol{\beta}_{t'}\|_1)$ - „LASSO“-penalty and $(\lambda \|\boldsymbol{\beta}_{t'}\|_2^2/2)$ - „Ridge“-penalty;
- $\lambda = 0$ - the objective function (1) leads to simple ordinary least squares(OLS) regression;
- $\alpha = 1$ - pure „LASSO“ method and $\alpha = 0$ - the pure „Ridge“ method;
- $\lambda$ is selected via cross-validation, which is a data driven method that optimizes out-of-sample predictive accuracy

# Dynamic forecast combination- rolling window estimation

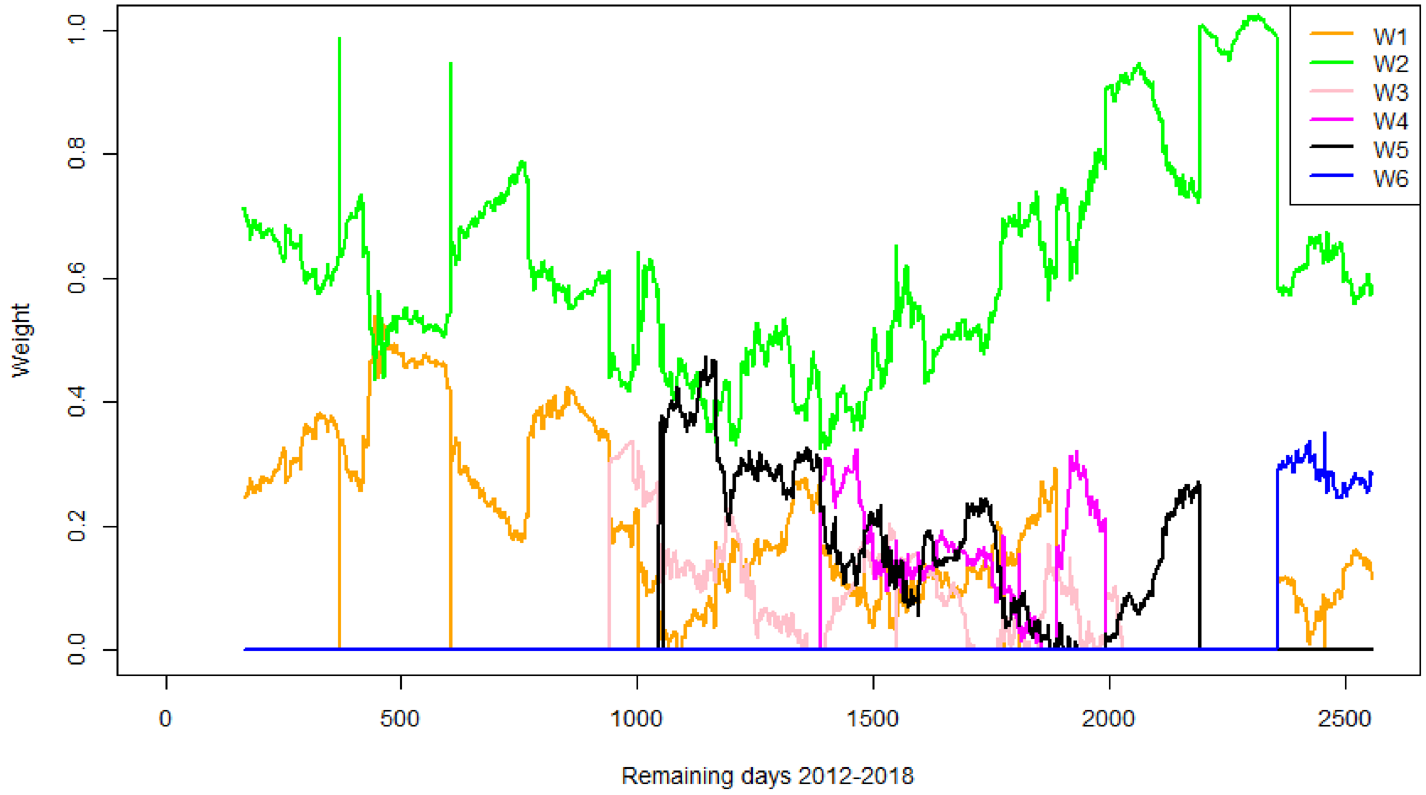
- The combined (meta) forecast:

$$\tilde{\varphi}_t = \beta_{0,t'} + \sum_{i=1}^{m} \beta_{i,t'}\tilde{\varphi}_{it} \qquad (2)$$

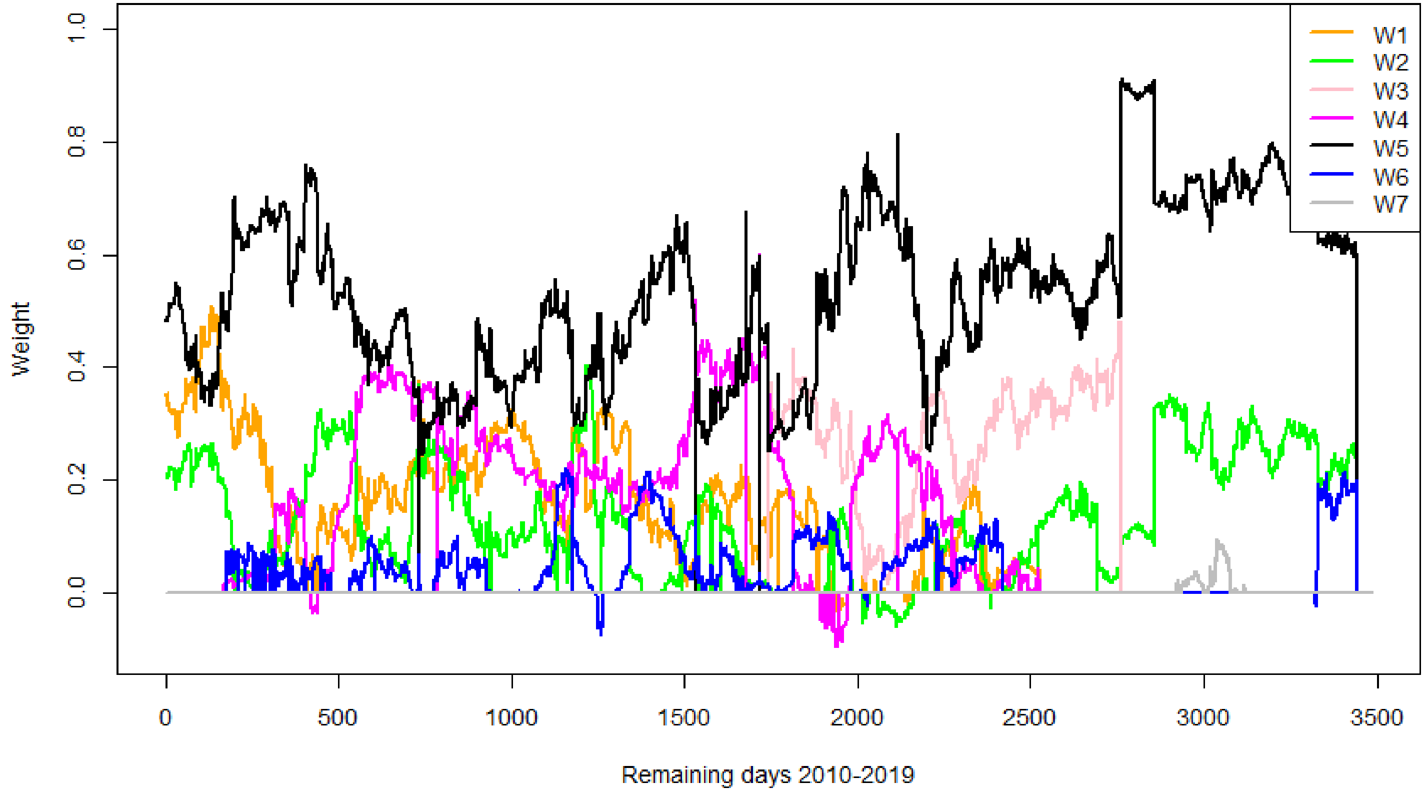
  - $\tilde{\varphi}_{it}$ are the $i = 1, \dots, \mathrm{m}$ individual forecasts at time $t$;
  - individual forecasts are combined through the coefficients $\beta_{0,t'}$ and $\beta_{i,t'}$ (combination weights)
  - the determination of the coefficients is based on historical information available up to the time point: $t \leq t'$



# Empirical results 1: Forecasts‘ combination weights-PV



# Empirical results 2: Forecasts‘ combination weights-wind



# Empirical results 3: PV forecasts‘ accuracy – yearly level

| PV | | | | | | |
|---|---|---|---|---|---|---|
| Year | Average feed-in [MW] | Average number of used forecasts | RMSE [MW] | | | |
| | | | SA | K | **DELNET** | F2 |
| 2012 | 584 | 2 | 218 | 213 | **184** | 193 |
| 2013 | 713 | 2 | 272 | 249 | **249** | 272 |
| 2014 | 836 | 3 | 256 | 295 | **249** | 263 |
| 2015 | 929 | 4 | 256 | 260 | **249** | 256 |
| 2016 | 980 | 5 | 261 | 249 | **237** | 240 |
| 2017 | 1.016 | 3 | 334 | 277 | **274** | 277 |
| 2018 | 1.276 | 2 | 337 | 263 | **269** | 272 |
| Overall | 905 | 3 | 283 | 263 | **245** | 255 |

- **DELNET is the forecast obtained with the Dynamic Elastic Net with Dynamic Data Pre-processing**
- Simple average (SA) is the forecast combination, in which each individual forecast obtains equal weight
- K is the combined forecast by 50Hertz
- F2 is the best individual forecast

# Empirical results 4: Wind forecasts‘ accuracy – yearly level

| Wind | | | | | | |
|---|---|---|---|---|---|---|
| Year | Average feed-in [MW] | Average number of used forecasts | RMSE [MW] | | | |
| | | | SA | K | **DELNET** | F5 |
| 2010 | 1.734 | 5 | 663 | 582 | **558** | 582 |
| 2011 | 2.107 | 5 | 580 | 579 | **556** | 576 |
| 2012 | 2.106 | 5 | 588 | 623 | **552** | 627 |
| 2013 | 2.113 | 5 | 601 | 598 | **590** | 605 |
| 2014 | 2.252 | 5 | 579 | 549 | **542** | 561 |
| 2015 | 3.156 | 6 | 717 | 684 | **656** | 688 |
| 2016 | 2.931 | 6 | 664 | 611 | **611** | 611 |
| 2017 | 3.735 | 4 | 755 | 733 | **716** | 728 |
| 2018 | 3.813 | 3 | 795 | 708 | **717** | 721 |
| Overall | 2.661 | 5 | 660 | 630 | **611** | 633 |

- **DELNET is the forecast obtained with the Dynamic Elastic Net with Dynamic Data Pre-processing**
- Simple average (SA) is the forecast combination, in which each individual forecast obtains equal weight
- K is the combined forecast by 50Hertz
- F5 is the best individual forecast

# Conclusions

- Forecast combinations with the Dynamic Elastic Net with dynamic data pre-processing (DELNET) outperform the simple average (SA) and best individual forecast benchmarks for both PV and wind
  - DELNET PV has RMSE which is 13.4 % lower than that of SA
  - DELNET Wind has RMSE which is 8 % lower than that of SA
- The DELNET forecasting model has been successfully applied to both PV and wind forecasting and could have wider use for individual power plants, smaller grid areas, systems, regions or other countries

# Thank you for your attention!

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# References




- 50Hertz Transmission GmbH, 2019. "Grid Data: Photovoltaics". https://www.50hertz.com/en/Transparency/GridData/Photovoltaics.
- Bordignon, S., Bunn, D.W., Lisi, F. and Nan, F., 2013. "Combining day-ahead forecasts for British electricity prices", Energy Economics, Volume 35, Pages 88-103, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2011.12.001.
- Kath, C. and Ziel, F., 2018. "The value of forecasts: Quantifying the economic gains of accurate quarter-hourly electricity price forecasts", Energy Economics, Volume 76, pp. 411-423, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2018.10.005.
- Käso, M., Müsgens, F. and Grothe, O., 2016. "Dynamic forecast combinations of improved individual forecasts for the prediction of wind energy," 13th International Conference on the European Energy Market (EEM), Porto, 2016, pp. 1–5.https://doi: 10.1109/EEM.2016.7521228.
- Nowotarski, J., Raviv, E., Trück, S. Weron, R., 2014. "An empirical comparison of alternative schemes for combining electricity spot price forecasts", Energy Economics, Volume 46, pp. 395-412, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2014.07.014.
- Perez, R., Lorenz, E., Pelland, S., Beauharnois, M., Van Knowe, G., Hemker, K., Heinemann, D., Remund, J. Müller, S.C., Traunmüller, W., Steinmauer, G., Pozo, D., Ruiz-Arias, J. A., Lara-Fanego, V., Ramirez-Santigosa, L., Gaston-Romero, M. and Pomares, L.M., 2013. "Comparison of numerical weather prediction solar irradiance forecasts in the US, Canada and Europe", Solar Energy, Volume 94, pp. 305–326, ISSN 0038-092X, https://doi.org/10.1016/j.solener.2013.05.005.
- Uniejewski, B., Nowotarski, J. and Weron, R., 2016. "Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting", Energies, 9, 621.
- Xiyun, Y. and Song, C., 2014. "A combination method in photovoltaic power forecasting based on the correlation coefficient," IEEE 5th International Conference on Software Engineering and Service Science, Beijing, 2014, pp. 706–709. https://doi.org/10.1109/ICSESS.2014.6933665.
- Yang, X., Liu, H., Zhang, B. and Chen, S., 2014. "A combination method for photovoltaic power forecasting based on entropy weight method". Taiyangneng Xuebao/Acta Energiae Solaris Sinica. 35, pp. 744–749.
- Zou, H. and Hastie, T., 2005. "Regularization and variable selection via the elastic net". J. R. Statist. Soc. B, 67, pp. 301–320.