Brandenburgische
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„Day-ahead Photovoltaic Power Forecasting: A Statistical Approach“

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Agenda

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

Forecast combinations

- Elastic net methodology for obtaining forecast combinations in the field of energy
- Applications of forecasts combination (with dynamic determination of the coefficients) to solar photovoltaic (PV) data
- Whether such PV feed-in forecasts combinations outperform:
  - individual forecasts
  - other benchmarks (such as simple average or linear regression)

Motivation

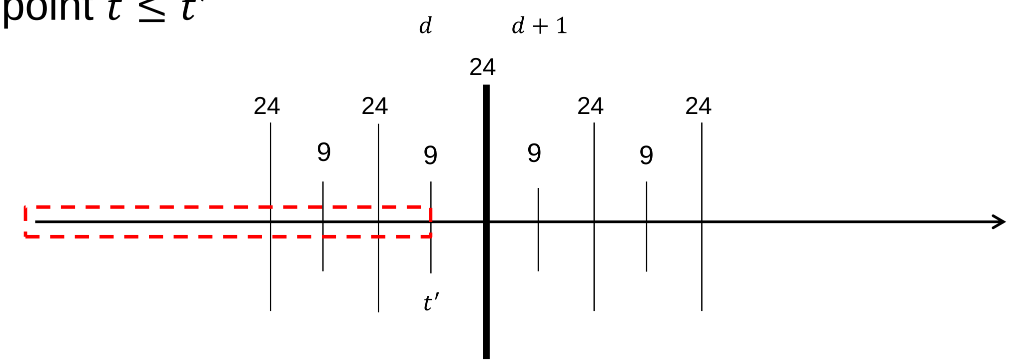
- Installed PV capacity in Germany was 45.9 GW and produced electricity from PV was 8.4 % of net electricity generated in 2018
- Precise PV feed-in forecasts aim to reduce the uncertianty related to this variable energy source
- Day-ahead PV feed-in forecasts are used by:
  - A) Plant operators (to manage power plants and to minimize penalties due to deviation between forecasted and produced energy)
  - B) System operators (to determine the reserve requirements and to meet real time loads)
  - C) Traders (to optimize their trading activities)

Rolling window estimation - dynamic forecast combination

- The combined forecast:

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

  - $\tilde{\varphi}_{it}$ 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 $t \leq t'$



Elastic-Net-Model (type of regularization)

- with highly correlated predictors, one important task is to decrease the model complexity 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

The following objective function is used as optimization criterion for estimating the model coefficients in the “elastic net” method (Zou and Hastie, 2005 and Friedman et al., 2010):

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

where $\beta 0,t'*$ and $\boldsymbol{\beta} t'*=\beta 1,t'*,\ldots,\beta m,t'*T$ are the optimal model coefficients;

$\boldsymbol{\varphi} tT=\varphi 1t,\ldots,\varphi mtT$ - includes the m different individual forecasts for each t from the historical time frame t'-$N+1,t'$;

φt represent the associated realizations of actual PV power

The elastic net contains a “penalization term”, which consists of „lasso“-penalty $(\lambda \boldsymbol{\beta} t'1)$ and „ridge“-penalty $(\lambda \boldsymbol{\beta} t'22/2)$;

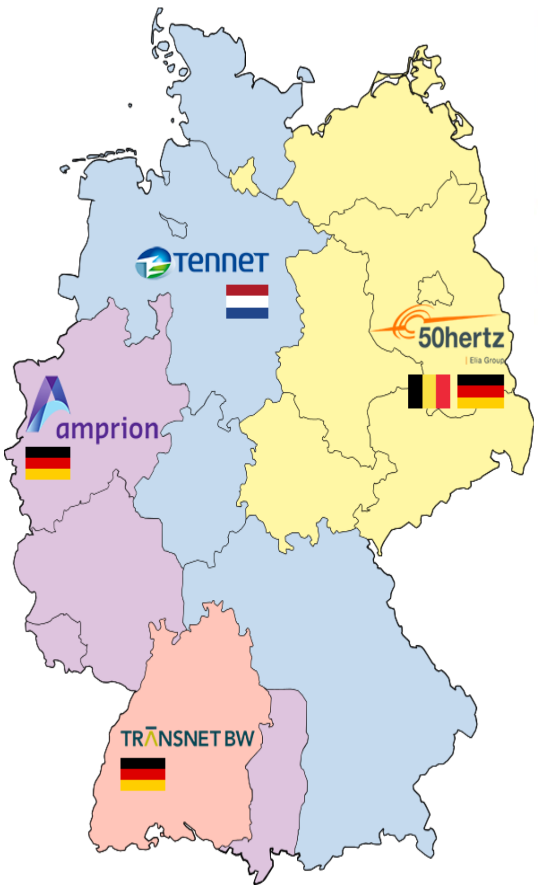
$\lambda=0$ means that the objective function (1) leads to simple OLS regression;

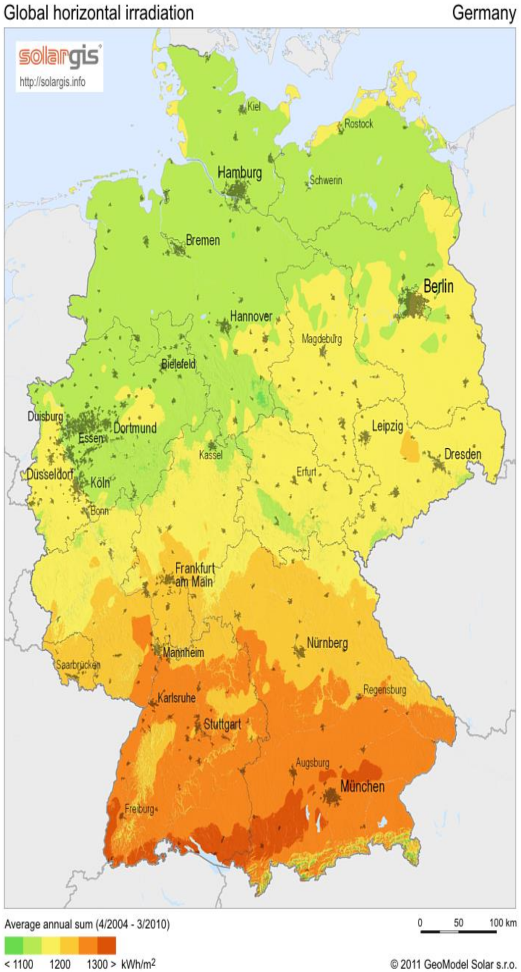
$\lambda>0$ controls the magnitude of the penalty term;

α gives higher weight to the „lasso“ or the „ridge“ regression method, whereas $\alpha=1$ is pure „lasso“ method and $\alpha=0$ is the pure „ridge“ method;

λ is selected via cross-validation, which is a data driven methods which optimizes out-of-sample predictive accuracy

Data





- obtained in cooperation with 50hertz, one of the German transmission system operators
- approximately 25 % of total installed PV capacity
- covers the period 2012–2018
- data is gathered in quarter-hourly intervals, totaling 245,472 observations of actual PV feed-in (in MW)
- day-ahead PV forecasts (at 9 a.m.) for feed-in as provided by the six different forecasts providers (F1–F6) as well as a combined forecast by 50Hertz (K)

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 is the actual photovoltaic feed-in
- K is the combined forecast by 50Hertz
- F1–F6 include the day-ahead 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

Dynamic pre-processing of the data

- Preprocessing of both historical data and next day forecasts

The following data is available:

- The past 15.780 forecast values as well as the day-ahead-forecasts (96 values) are checked for:
  - Impossible values
  - Values repetitions
  - Missing values

Forecasts accuracy – yearly level

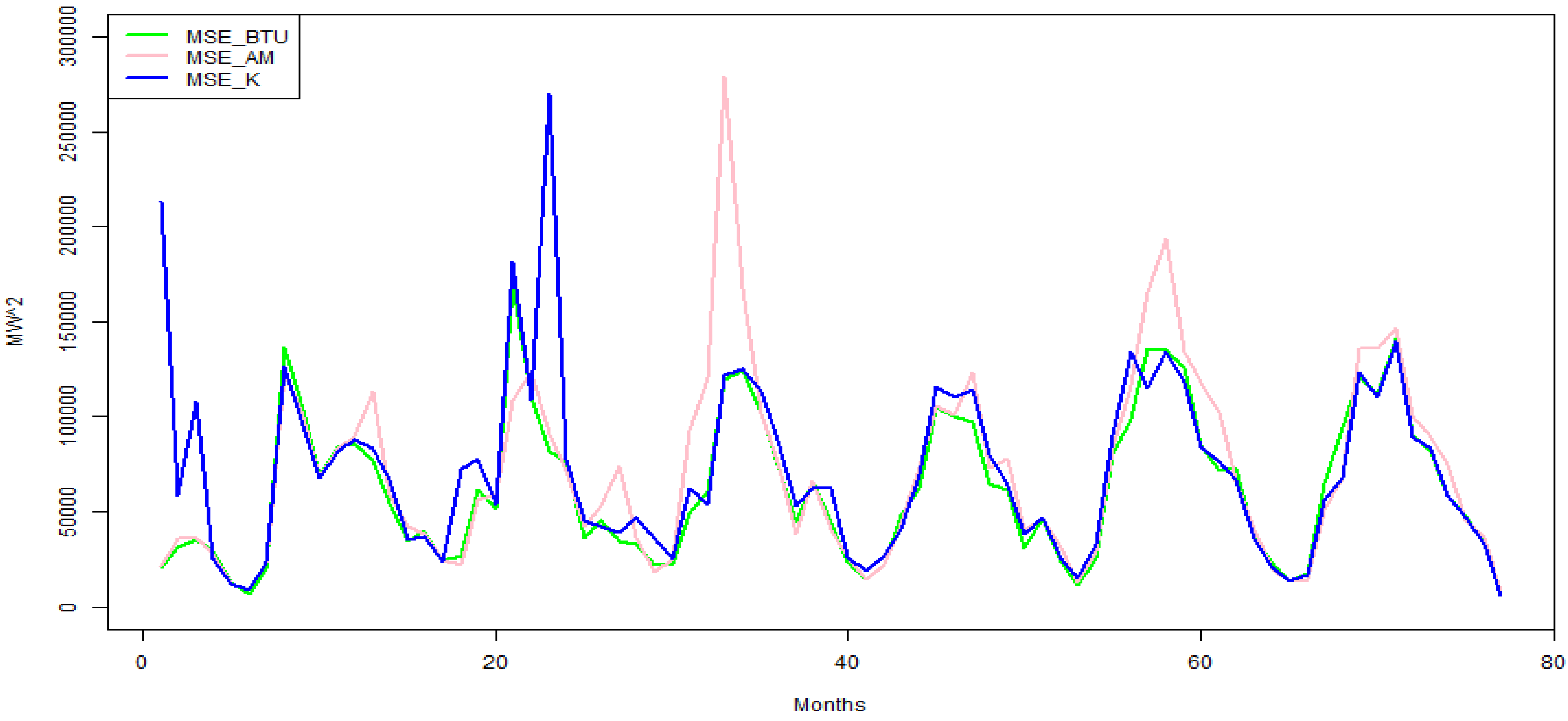
Mean Squared Error: $MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^2$;

Skill score: $SS = \frac{MSE_{reference} - MSE_{forecast}}{MSE_{reference}}$

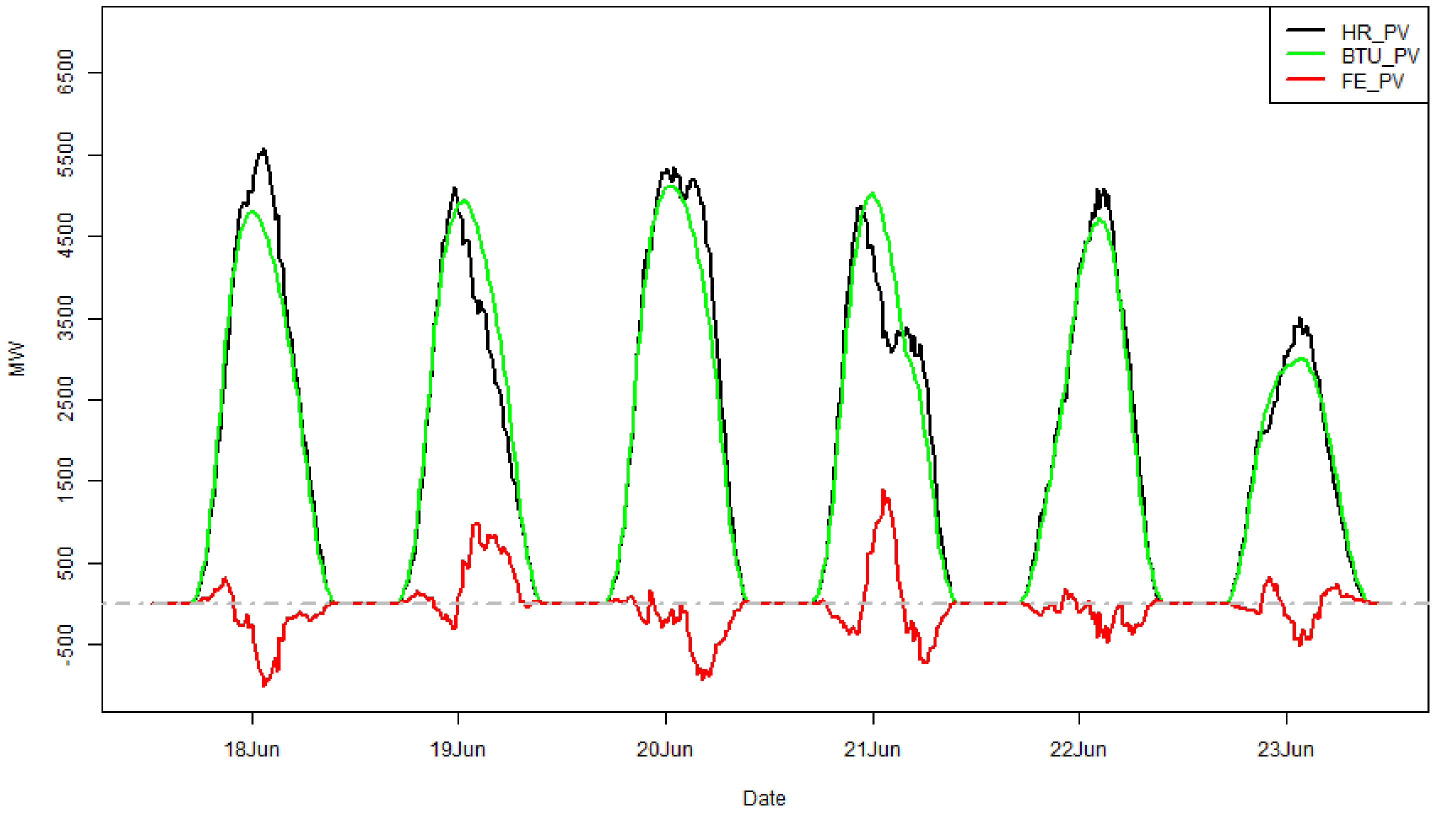
Year	MSE [MW²]					SS (of BTU relative to)			
	BTU	AM	OLS	K	F2	AM	OLS	K	F2
2012	**33.986**	35.307	33.998	928.861	37.251	0,04	0,00	0,96	0,09
2013	**61.803**	64.917	62.100	61.992	74.025	0,05	0,00	0	0,17
2014	**62.216**	63.008	62.658	87.118	68.964	0,01	0,01	0,29	0,1
2015	**62.062**	87.116	61.926	67.629	65.572	0,29	0,00	0,08	0,05
2016	**56.208**	62.710	56.011	62.160	57.720	0,1	0,00	0,1	0,03
2017	**75.200**	90.285	75.657	76.776	76.497	0,17	0,01	0,02	0,02
2018	**72.234**	75.501	72.617	69.181	74.155	0,04	0,01	-0,04	0,03
Overall	**62.348**	70.688	62.539	173.844	64.870	0,12	0,00	0,64	0,04

- **BTU is the forecast obtained by the dynamic elastic net regression**
- Arithmetic mean (AM) is the combination where each forecast obtains equal weight
- OLS is the combination obtained via ordinary least squares
- K is the combined forecast by 50Hertz
- F2 is the best day-ahead forecast

Monthly forecasting errors (MSE)



BTU forecast vs actual observation in June 2018



Conclusions

- Using rolling window estimation, with time-varying coefficients and cross validation improves the precision and out-of-sample forecasting ability
- Forecast combinations with the elastic net (BTU) outperform the AM benchmark as well as individual forecasts
  - *Accuracy:* the MSE of BTU is 12 % lower than that of AM and 4 % lower than the best individual forecast (F2)
  - *Sensitivity:* BTU predicts the sign of change correctly in 92.3 % of the cases whereas AM in 82.2%
- The dynamic elastic net forecasting model could be applied for other renewable energy types and have wider use also for individual power plants, systems, regions or other countries

Thank you for your attention!

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Appendix I: Data pre-processing

Pre-processing of forecasts - 96 values // historical forecasts data - past 15840 observations

- 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)

Appendix II: Combination weights