KTH ROYAL INSTITUTE
OF TECHNOLOGY

Modelling wind power from reanalysis data: A review of datasets, methods and results

Note that all results are preliminary!

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Scope

Using (possibly downscaled) reanalysis data for modelling sub-daily, area aggregated wind power output.

Other wind power applications:

Long-term correction

Resource assessment

Calculations for single sites

Climate change impact

E.g. monthly values

Wind speed or WPD

Basics

Reanalysis data

Wind farm database and power curves

Wind speed @ hub height

Wind farm output

Aggregate

1. Long time series (40 years or more)
2. Generally good validation results
3. Can be used for future scenarios

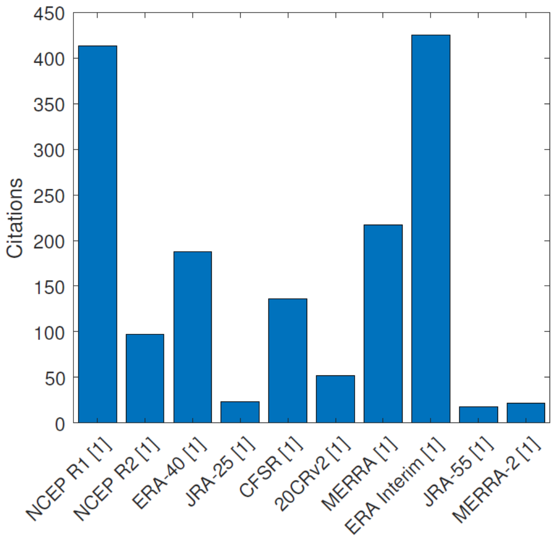
A short history

- Early works (2000-2001) by G. Giebel and G. Czisch
- A few major projects 2005-2010 (WWSIS, EWITS, TradeWind, dena)
- Some more papers from around 2010
- A lot since 2015

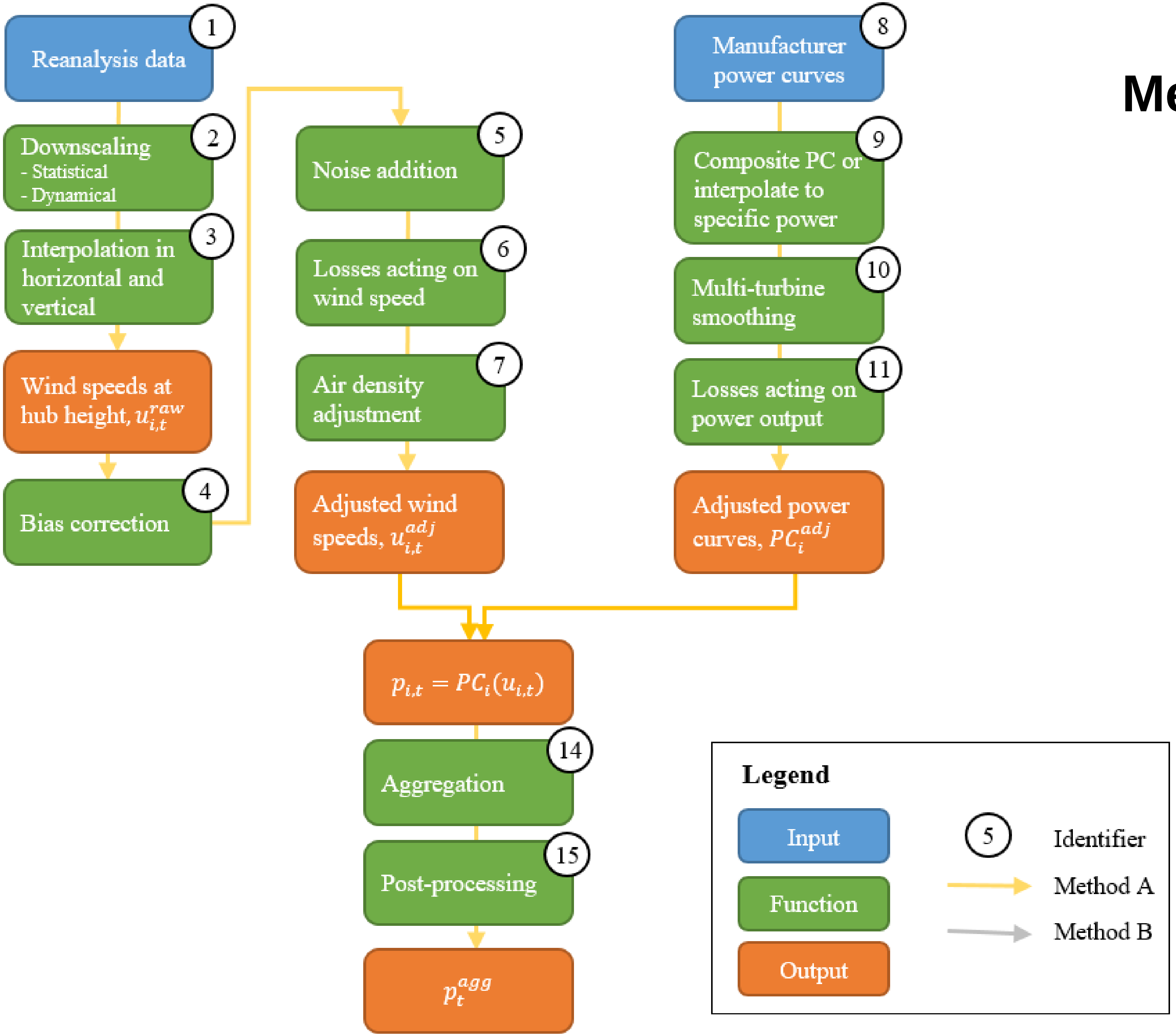
Alternatives include upscaling of historical observations, (10m) met masts or purely statistical methods.

Datasets

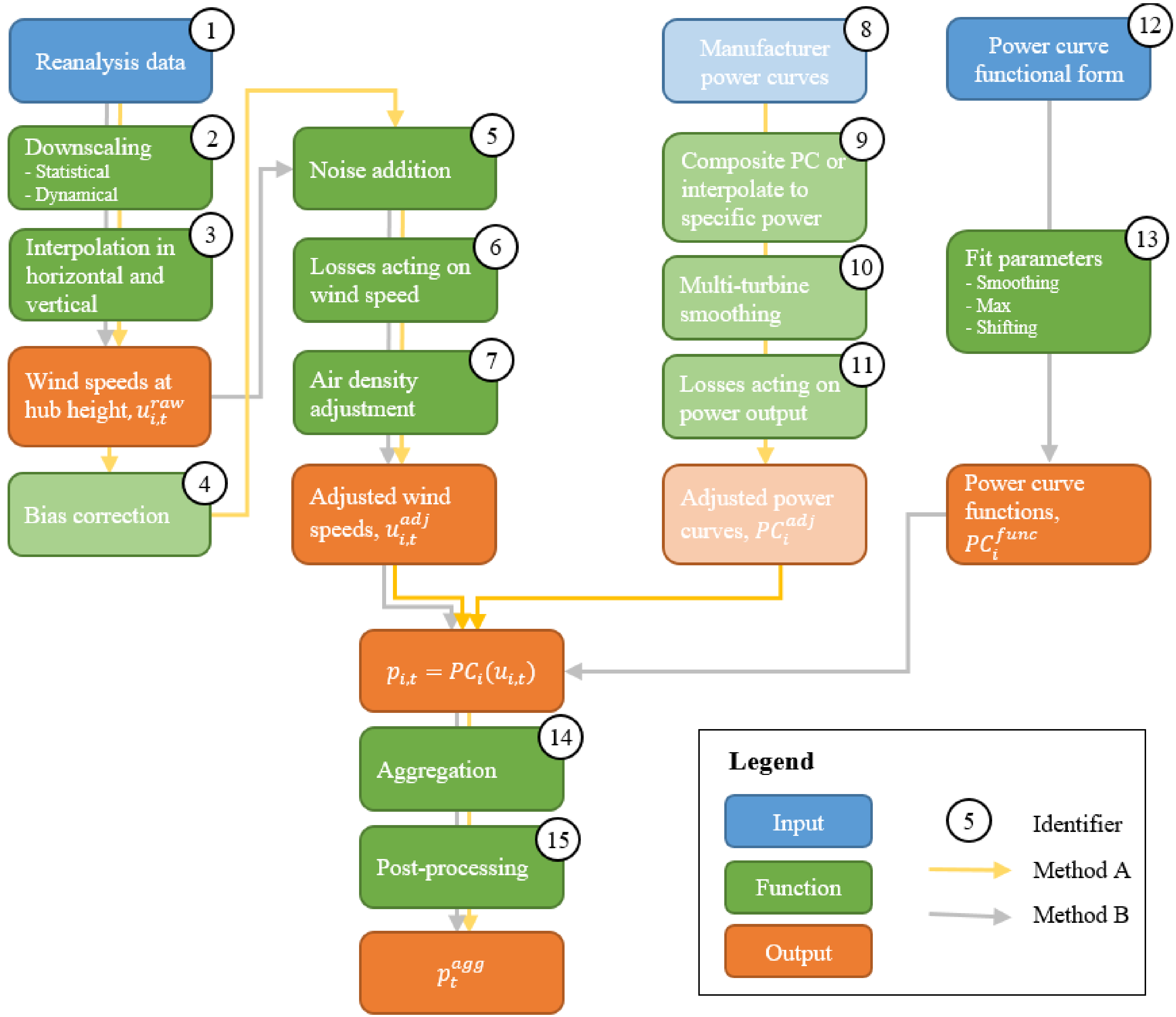
Institute	Name and Ref.	Time range	Time res.	Spatial res.
NCEP	R1 [3]	1948 –	6 h	2.5°
NCEP	R2 [4]	1979 –	6 h	2.5°
ECMWF	ERA-40 [5]	1957 – 2002	6 h	1.125°
JMA	JRA-25 [6]	1979 – 2004	6 h	1.25°
NCEP	CFSR [7]	1979 – 2010	1 h	0.5°
ECMWF	ERA-Interim [9]	1979 –	6 h	79 km
NASA	MERRA [10]	1979 –	1 h	$1/2 \times 2/3°$
NOAA	20CRv2c [11]	1851 – 2014	6 h	2.0°
JMA	JRA-55 [12]	1958 –	3 h	1.25°
ECMWF	ERA-20C [13]	1900 – 2010	3 h	125 km
ECMWF	CERA-20C	1901 – 2010	3 h	125 km
NASA	MERRA-2 [1]	1979 –	6 h	$0.5 \times 0.625°$
ECMWF	ERA5	1979 –	1 h	31 km



Methods



1 Reanalysis data
2 Downscaling
- Statistical
- Dynamical
3 Interpolation in horizontal and vertical
Wind speeds at hub height, $u_{i,t}^{raw}$
4 Bias correction
5 Noise addition
6 Losses acting on wind speed
7 Air density adjustment
Adjusted wind speeds, $u_{i,t}^{adj}$
8 Manufacturer power curves
9 Composite PC or interpolate to specific power
10 Multi-turbine smoothing
11 Losses acting on power output
Adjusted power curves, PC_i^{adj}
$p_{i,t} = PC_i(u_{i,t})$
14 Aggregation
15 Post-processing
p_t^{agg}
Legend
Input
Function
Output
5 Identifier
Method A
Method B



Reanalysis data
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Manufacturer power curves
8
Composite PC or interpolate to specific power
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Multi-turbine smoothing
10
Losses acting on power output
11
Adjusted power curves, PC_i^{adj}
Power curve functional form
12
Fit parameters
- Smoothing
- Max
- Shifting
13
Power curve functions, PC_i^{func}
$p_{i,t} = PC_i(u_{i,t})$
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Post-processing
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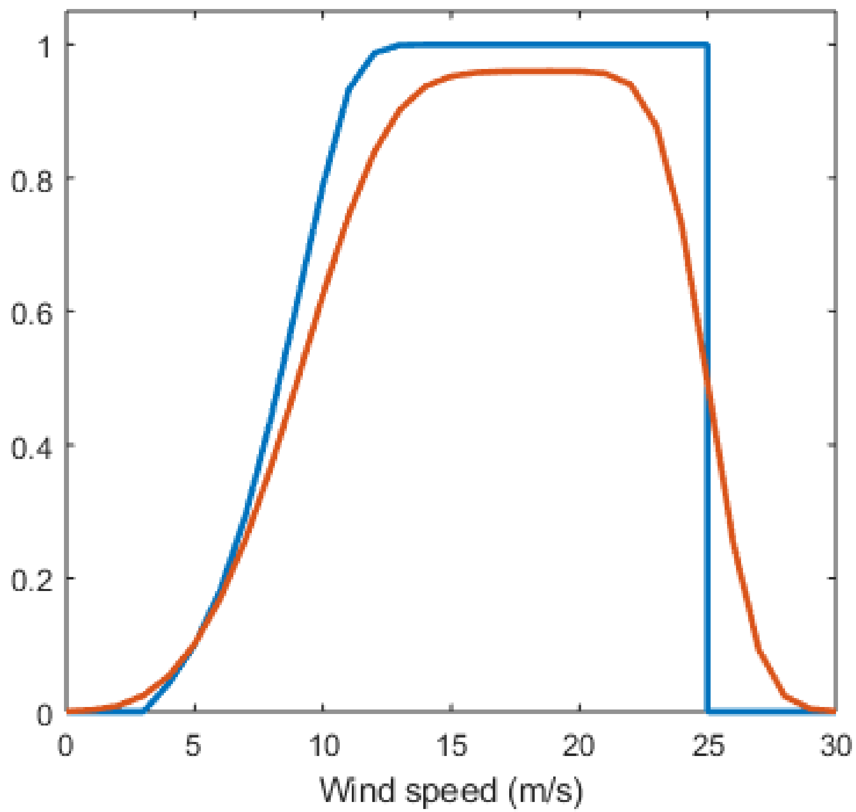
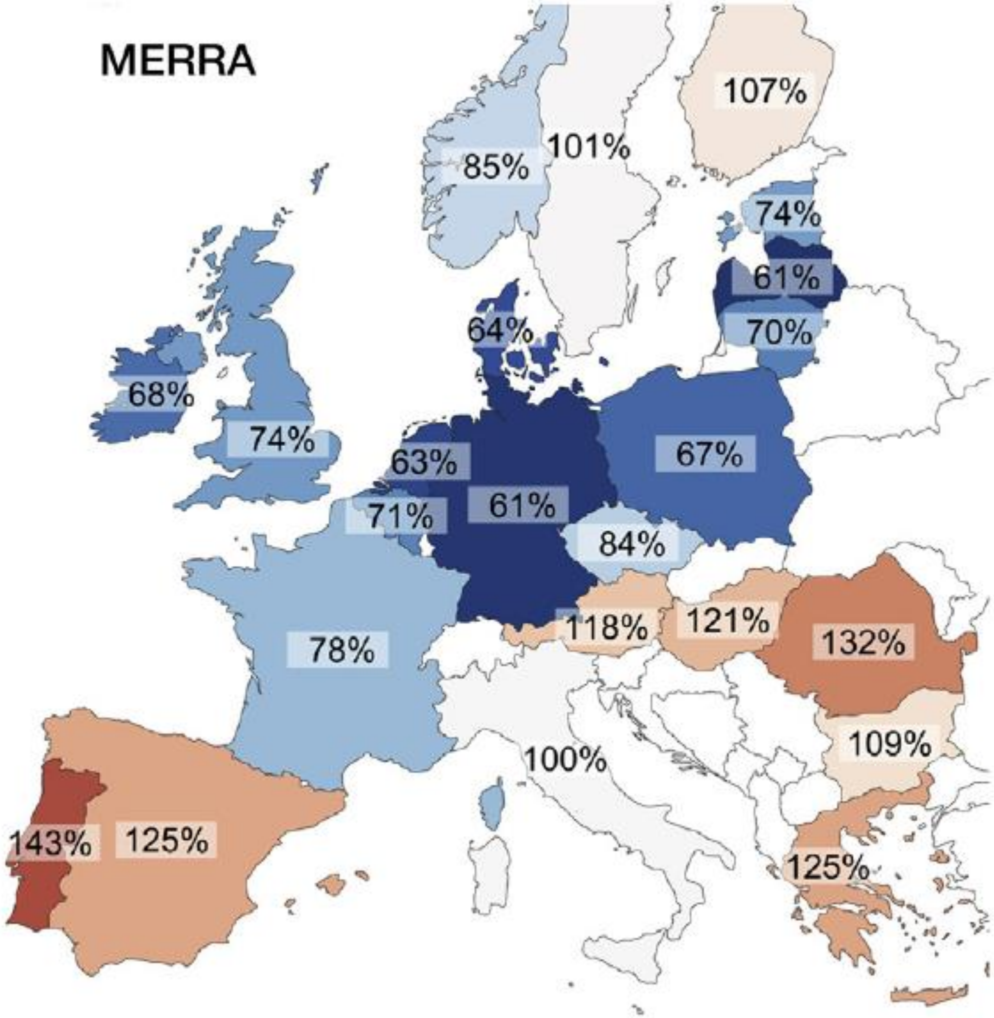
Power curve



Methods (~75 papers)

- No methodology consensus, large differences in model complexity
- MERRA(2) and ERA-Interim
- Downscaling used by ~1/3 (WRF, COSMO)
- Power and log law most common
- Air density rarely taken into account
- Many different forms of PCs used, relatively often with smoothing
- Losses surprisingly often neglected completely
- Bias correction used by around 1/3
- Validation (>50%, only 25% P_{agg})

Bias correction



- Not due to poor method (e.g. neglected losses)
- Regional bias (and also local of course)
- Not resolved by using COSMO or GWA

(Downscaled) reanalyses:

- Good time patterns
- Poor mean if not bias-corrected

Results Europe (correlations)

Correlations		DE	DK	UK	IE	FR	ES
Aigner 2011	COSMO EU	0,92	0,94				
	COSMO DE	0,93					
Cannon 2015	MERRA			0,96			
Cradden 2017	MERRA			0,957			
Gonzalez 2017	MERRA	0,971	0,952	0,863	0,964	0,952	0,916
	MERRA and GWA	0,972	0,957	0,855	0,965	0,959	0,913
Henckes 2018	COSMO-REA6	0,97					
Olauson 2018	MERRA	0,982	0,973			0,975	
	ERA5	0,987	0,973			0,982	
Staffell 2016	MERRA	0,981	0,955	0,967		0,956	0,917
Monforti 2017	MERRA	0,986	0,962			0,973	0,955
Nuno 2018	ERA-I and WRF	0,931					0,921
Kubik 2013	MERRA				0,911		
Vautard 2014	ERA-I and WRF	0,89	0,90	0,92	0,91	0,90	0,85
Bitetti 2018	ERA5		0,970				

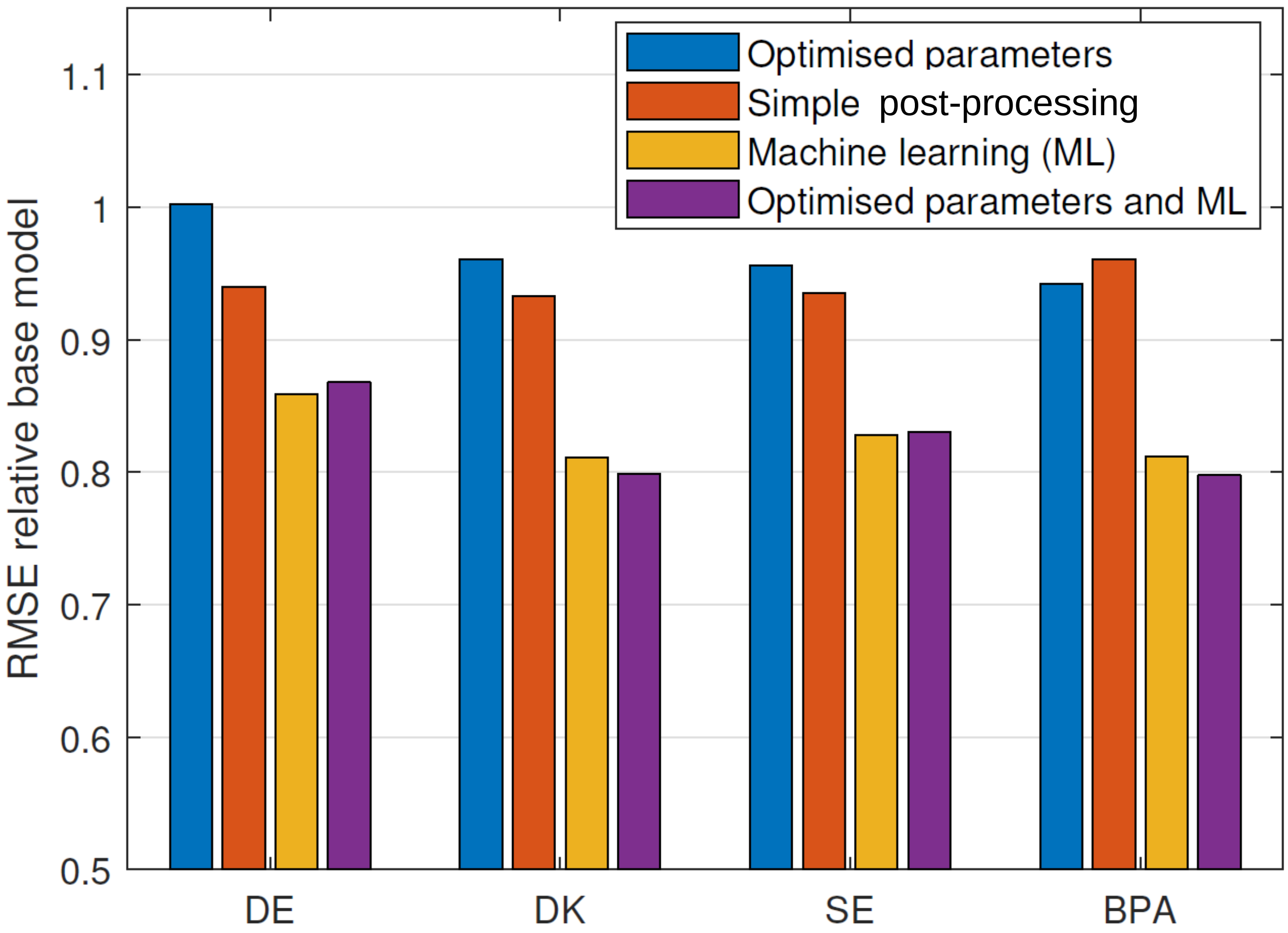
Patterns in results

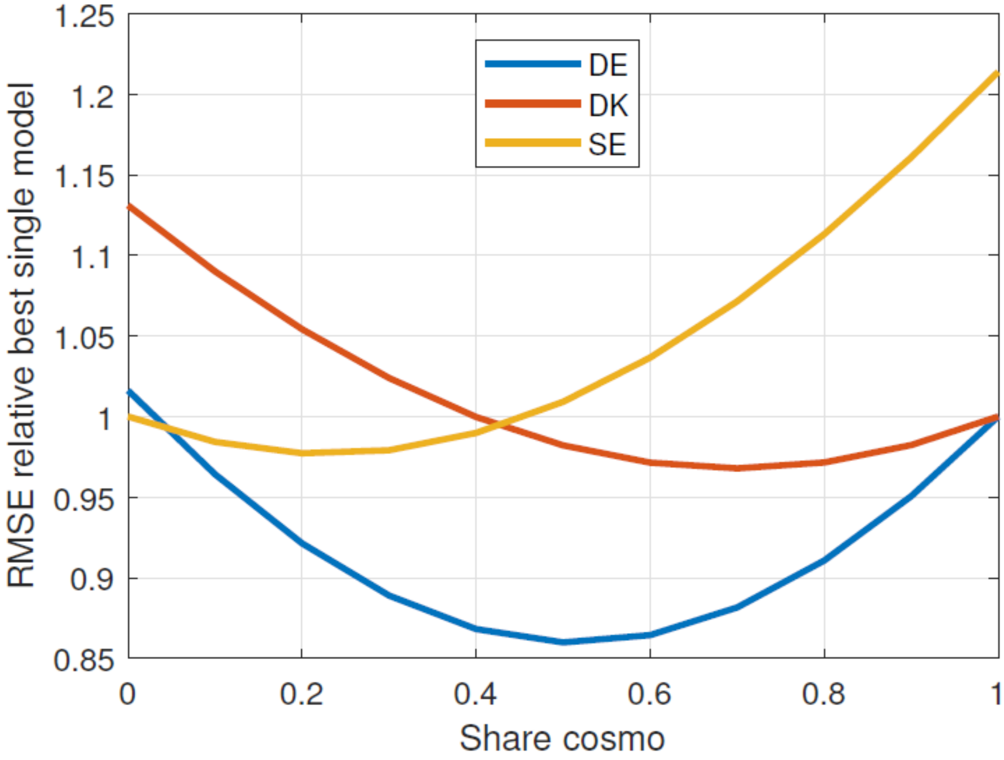
Linear model: correlation(country, year, downscale)

Be cautious; many other important factors...

- Results have improved over time
- Some countries are easier to model (large installed capacity, large area, flat terrain, good data quality)
- Downscaling does not improve results, rather the opposite. This conclusion is strengthened by a few comparative studies.

A little study





RMSE relative best single model
Share cosmo
DE
DK
SE
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
0.85
0
0.2
0.4
0.6
0.8
1

Conclusions

- Most important tool today; global, free and good results (for countries)
- Methods differ significantly
- Bias-correction and validation of P_{agg} very important
- Better results with newer reanalyses (ERA5 probably best today)
- Downscaling seems superfluous (for countries)
- Learning from forecasting community may improve results further

Bonus: Synthetic wind power forecasts

Olauson et al 2016, A New Approach to Obtain Synthetic Wind Power Forecasts for Integration Studies

Actual generation (measurements) – Operational forecasts = Actual FEs

Modelled FEs

Tricky with statistical approach, eg multivariate ARMA (although good attempts have been made):

- FEs depend on site, horizon, wind speed and met conditions
- Complicated correlations between sites (distance, horizon and more)
- Level and phase errors
- FEs from consequtive forecasts not independent

New approach

Actual generation (measurements) − Operational forecasts = Actual FEs

Modelled generation (MERRA) − Synthetic forecasts (GEFS) = Modelled FEs

	Operational model and current data	Consistent model and historical data
Nowcast	Analysis	Reanalysis
Forecast	Forecast	Reforecast

Results

- Distribution
- Spectrum
- Horizon dependence

- Site dependence
- Phase errors
- More realistic for future scenarios(?)
- GEFS only once per day, quite a lot of data