

Exploring the value of statistical post-processing of s2s predictions for energy applications

Paula LM Gonzalez paula.gonzalez@metoffice.gov.uk

With contributions from: Hannah Bloomfield, David Brayshaw, Andrew Charlton-Perez, Florian Ziel

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pre-positioning of disaster response materials

implement irrigation, pesticide or fertilizer

schedules

Motivation

- Climate information on sub-seasonal timescales is needed for decision making.
- Grid point forecasts have limited skill at lead times greater than 1 week.
- Therefore sub-seasonal forecasts have had limited use in industry.
- S2S forecasts could help address:
 - wind power intermittency
 - Hedging for peak demands
 - Grid operation optimisation of energy prices
 - Nuclear power maintenance schedules



- revise water allocations
- activate water conservation practices



How can post-processing help with some of this limiting factors? Discussion from S2S BOG during **Next Generation Challenges in Energy Climate Modelling** (NextGenEC 2021)

What limits the use of a new forecast product?



https://research.reading.ac.uk/met-energy/next-generation-challenges-workshop/



Contributions



• Met-to-energy conversion of forecasts

Sub-seasonal forecasts of demand and wind power and solar power generation for 28

European countries

HC Bloomfield, DJ Brayshaw, PLM Gonzalez, A Charlton-Perez Earth System Science Data 13 (5), 2021

• Pattern-based predictions

Pattern-based conditioning enhances sub-seasonal prediction skill of European national energy variables

HC Bloomfield, DJ Brayshaw, PLM Gonzalez, A Charlton-Perez Meteorological Applications 28 (4), 2021

• ML-based multi-model combinations

<u>A new approach to extended-range multimodel forecasting: Sequential learning algorithms</u>

PLM Gonzalez, DJ Brayshaw, F Ziel

Quarterly Journal of the Royal Meteorological Society 147 (741), 4269-4282

Example: wind & demand – ECMWF system





<u>Conzalez, Paula, Bloomfield, Hannah, Brayshaw, David</u> and <u>Charlton-Perez, Andrew</u> (2020): Sub-seasonal forecasts of European electricity demand, wind power and solar power generation. University of Reading. Dataset. <u>https://doi.org/10.17864/1947.275</u>

S2S skill: Demand wk1-4





S2S skill: energy vars

- ECMWF is generally better than NCEP (when ERA5 is truth)
- Forecasts perform best for demand (dependent on countryaverage temperature)
- Lower skill seen for wind and solar power generation (dependent on 100m wind speed and surface irradiance)

S2S



S2S skill: demand ECMWF

- Skill decays with the complexity of the skill metric, therefore users need to think about what information is useful at different lead times to action decisions
- Increased skill in Northern and Eastern Europe
- Generally, these forecasts are not that bad!



Pattern based methods

- Pattern based forecasts might provide more skill at extended lead times.
- Two types of patterns are examined in this study:
 - Weather Regimes (see Cassou 2008)
 - Targeted Circulation Types (see Bloomfield et al., 2020)







(i)

(e)_

-2 -1

MSLP

Residual load

← Weather Regimes

Shown to have good S2S predictability, but they have poor discrimination of energy



Pattern-based forecasts of demand



- Predictability of weather regimes and TCTs in ECMWF and NCEP hindcasts is limited, but there are improvements over the grid point forecast in weeks 3-4.
- Further **improvements** in skill may be seen with refinement of the method (mainly associated with the **pattern assignment**)



Pattern based conditioning of demand





ML-based multi-model combination



- Abundance of S2S systems available → try to gain skill through a 'smart' combination of their predictions.
- Standard multi-model combination → 'static' weights (typically, uniform or skill-based weights) → ignores changing skill of the forecasting systems (e.g., seasonal, model updates, state dependence)

Online prediction with expert aggregation / sequential learning:

- a family of machine learning algorithms that allow to **combine predictors or 'experts' with evolving weights** by progressively minimizing a loss function.

Advantages of online methods:

→ multi-model combination → adjusts to preserve skill (minimize loss) under certain conditions. → different mixture of the experts can be trained for different quantiles of the distribution and obtain a robust 'forecasting system'.

→ **unsuitable experts** are automatically **discarded by the method**.

ML-based multi-model combination



EXPERTS								
	ENSEMBLE BASED	 QUANTILES of the ensemble distribution: q10,q35,q50,q65,q90 (for each S2S ensemble) 						
		 FCST_MX (captures seasonality and range of models) FCST_MN 						
	REANALYSIS BASED	 QUANTILES of the climatology (ERA5 1.5 deg – 11yrs as loo): q10,q35,q50,q65,q90 						
		 PERS (persistence of weekly value for forecast days -7 to 0) PERS_1yr (persistence of past-year weekly demand) 						
		 SEAS_MX (captures seasonally-varying range of obs) SEAS_MN 						
REFERENCE FORECASTS								
		 UNIF_NWP (uniform combination of ECMWF & NCEP) CLIMATOLOGY (estimates for full Qgrid from 11yrs loo) ORACLE_NWP_linear (optimal mixture of models – full period) ORACLE_NWP_convex (requires 0<wi<1 &="" sum(wi)="1)</li"> </wi<1>						



Two experiments:

- full: considering all experts
- NWP-only: considering only the experts from the hindcast systems

Deterministic skill – UK demand



Sequential learning algorithms do better, in particular at longer lead times

Average weights evolutions



Reanalysis-based 'experts' become more relevant for longer lead times

Probabilistic skill – UK demand



Improvement

Sequential learning algorithms show improvements in the distribution

Probabilistic skill – UK demand

relative to equal (b) Q-mean improvement relative to EW_NWP weights (ratio) UK Demand - years 4-12 (2002-2010) 1.5 wk1 wk2 Quantile-mean wk3 Pinball loss ratio to EW_NWP 60 wk4 pinball loss → -CRPS wk5 \boxtimes Results suggest that there is a skill improvement associated with incorporating reanalysisbased predictors O_NWP_lin O_NWP_conv EGA BOA BOA_NWP EW_NWP ECMWF EMOS NCEP CLIM EGA_NWP

Improvement

Sequential learning algorithms do better, in particular at longer lead times

Are the skill improvements significant?

Sequential learning method generally better than equal weight combinations

EGA some advantage over BOA at long lead times

Significant improvement from incorporating reanalysis-based experts at longer lead times **TABLE 2.** Results from a Diebold–Mariano significance test applied to pairs of UK electricity demand forecasts

Comparison	Week 1	Week 2	Week 3	Week 4	Week 5
BOA versus EW_NWP	<0.001	<0.001	<0.001	<0.001	<0.001
EGA versus EW_NWP	<0.001	0.042	<0.001	<0.001	<0.001
BOA_NWP versus EW_NWP	<0.001	<0.001	<0.001	<0.001	<0.001
EGA_NWP versus EW_NWP	<0.001	<0.001	0.028	<0.001	<0.001
EGA versus BOA	1.000	0.781	0.001	0.002	0.037
BOA versus BOA_NWP	0.760	0.982	<0.001	<0.001	<0.001
EGA versus EGA_NWP	0.992	0.694	<0.001	<0.001	0.022

Similar results for other countries and for wind power forecasts !

Final discussion points

- S2S forecasts are relevant for energy-relevant decision making
- Grid-point skill is limited to ~1 week, but statistical post-processing has been shown useful to extend it
- In addition to extending skill, post-processing is useful to create tailored and friendly products for each specific application
- The research I presented is a few years old, and uptake of S2s forecasts has been growing
- Important to be aware that skill might be restricted to windows of opportunity, in particular for extremes

Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe DIV Domeisen, CJ White, H Afargan–Gerstman... – Bulletin of the American Meteorological Society, 2022



Thanks for listening!

Industry Consultancy – Met Office, UK



www.metoffice.gov.uk



paula.gonzalez@metoffice.gov.uk

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