Multivariate Postprocessing of Temporal Dependencies with Autoregressive and LSTM Neural Networks

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Aim

Aim: postprocess hourly wind speed forecasts from the 0h to the 48h lead time *simultaneously*, by issuing a multivariate forecast distribution and exploiting the temporal dependency in the forecasts.

We use a new statistical model, the ARMOS(p) model, and experiment with Recurrent Neural Networks for parameter estimation.

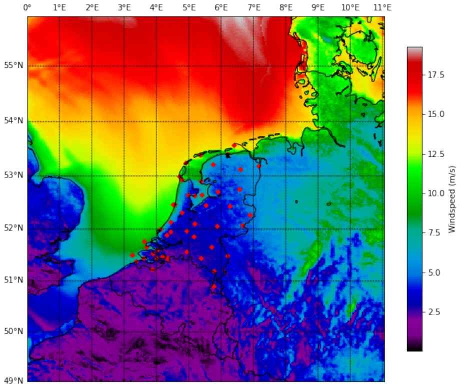


Figure: HA40 wind speed forecasts for 2015/01/01, 48h lead time. Red dots represent weather stations.

Data and Benchmark

Data:

- Observations from stations in the Netherlands;
- Predictors from HA40;
- 48 consecutive lead times;
- 3 years training data, 1 year test data.

Benchmark: EMOS + Schaake Shuffle

- EMOS: estimate parameters μ_t, σ_t^2 of marginal forecast distributions

$$W_t \sim \mathcal{N}_0(\mu_t, \sigma_t^2).$$

- Schaake Shuffle: *empirical copula* method, uses the marginals and historical data to output a multivariate forecast distribution.

New approach: ARMOS(p)

Möller and Groß [2016]: assumes the forecast errors follow an AR(p) process.

Estimate parameters $\mu_t,\ \sigma_t^2,\ \phi_j$ of the forecast distribution

$$W_t | W_{t-1}, \ldots, W_0 \sim \mathcal{N}_0 \left(\mu_t + \sum_{j=1}^{p} \phi_j (W_{t-j} - \mu_{t-j}),\ \sigma_t^2 \right)$$

ϕ_j introduce interactions between lead times. We get an explicit multivariate forecast distribution.

Experiments

Linear models

Global $\times$ Local models.

- EMOS/SS
- ARMOS(1)
- ARMOS(2)
- ARMOS(3)
- ARMOS(...)/SS

Network models

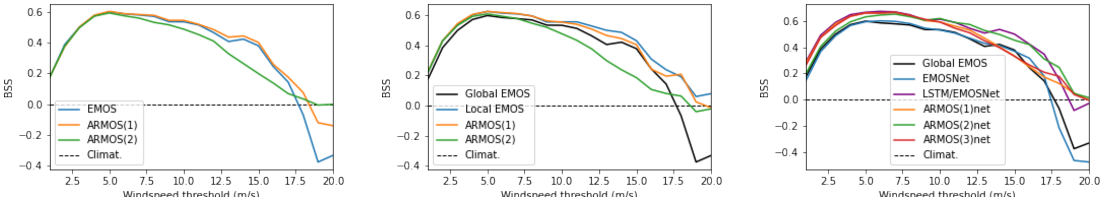
- EMOS/SS
- LSTM/EMOS/SS
- ARMOS(1)
- ARMOS(2)
- ARMOS(3)
- ARMOS(...)/SS

Results: multivariate verification scores

	Global linear			Local linear			Global network		
	LS	ES	VS	LS	ES	VS	LS	ES	VS
EMOS/SS	82.73	6.23	17.52	78.10	6.19	17.30	80.05	6.10	17.86
LSTM/EMOS/SS	-	-	-	-	-	-	72.60	**5.61**	16.52
ARMOS(1)	77.06	7.08	23.14	73.81	6.40	21.92	61.17	5.75	16.24
ARMOS(2)	72.07	7.28	19.43	70.03	6.92	19.06	**60.54**	5.73	**16.08**
ARMOS(3)	72.40	9.87	18.32	70.19	7.88	18.08	61.05	5.74	16.48
ARMOS(1)/SS	-	6.80	18.89	-	6.60	19.03	-	5.84	17.53
ARMOS(2)/SS	-	7.03	17.41	-	7.12	17.65	-	5.80	17.68
ARMOS(3)/SS	-	8.95	21.26	-	8.09	19.11	-	5.85	17.42

Table: Average value of the Logarithmic Score (LS), Energy Score (ES) and Variogram Score (VS) over the test set.

Results: marginal +48h BSS



(a) Global (b) Local (c) Network

Figure: Brier Skill Scores for the 48h lead time.

Conclusion

Conclusions...

- Global Linear Models $<$ Local Linear Models $<$ Global Network Models;
- LSTM/EMOSnet/SS and ARMOS(2)net are the best overall;
- EMOS is better on the margins, but ARMOS is better with dependencies;

In further work...

- Experiment with network architecture (ResNet, ConvLSTM, ...);
- and with other forecast distributions (Log Normal, Weibull).
- Compare with other benchmark models (QRF).

Bibliography

Annette Möller and Jürgen Groß. Probabilistic temperature forecasting based on an ensemble autoregressive modification. *Quarterly Journal of the Royal Meteorological Society*, 142 (696):1385–1394, 2016.

Daniel Tolomei. Multivariate postprocessing of temporal dependencies with autoregressive and lstm neural networks. Master's thesis, University of Utrecht, 2022. URL `https://studenttheses.uu.nl/handle/20.500.12932/41500`.