Space-time trajectories from probabilistic solar forecasts

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Outline

- What are space-time trajectories?
- Why do we need space-time trajectories?
- Space-time trajectory generation
- Space-time trajectories from probabilistic forecast
- Probabilistic and multivariate forecast assessment
- Results
- Conclusions

What are space-time trajectories?

The most common space-time trajectories are constantly issued by meteorological institutions in the form of ensemble forecasts.

The figure shows temperature time-trajectories at a single grid point generated by the 10 ensemble members of MEPS.

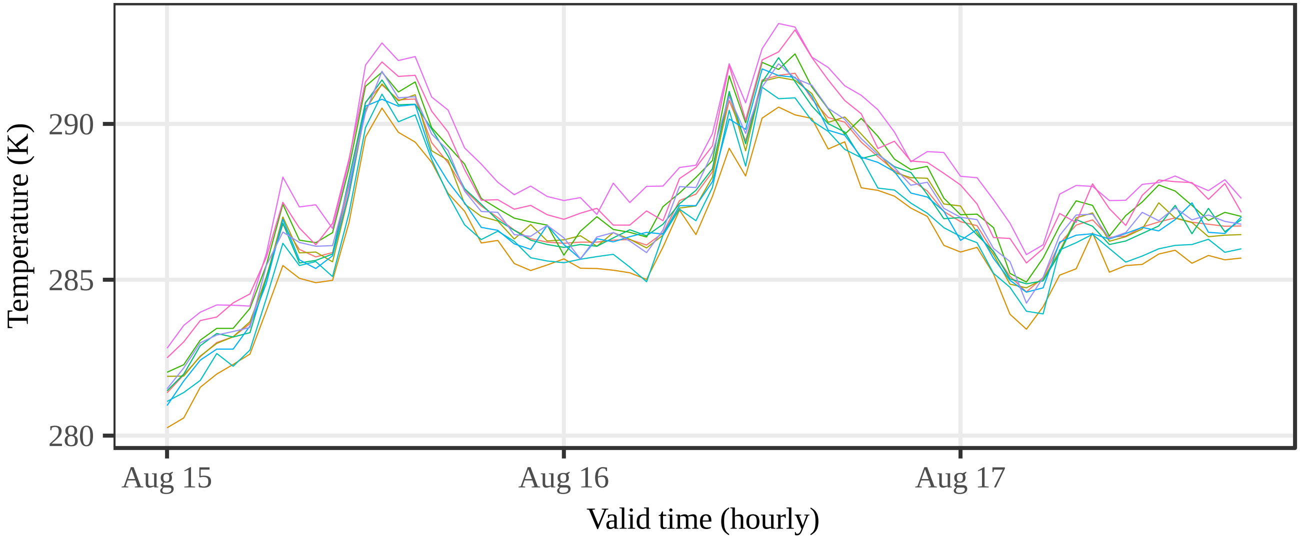


Figure: MetCoOp Ensemble Prediction System, issued 2019-08-15T00:00:00Z for Uppsala, Sweden

Why do we need space-time trajectories?

Because the spatio-temporal dependence structure provides essential information to operational decision problems [1], for instance:

- Electricity market participation.
- Power system reserve quantification.
- Stochastic model predictive control.
- Probabilistic power flow simulations.

Space-time trajectories from probabilistic forecasts

- A regression or machine learning model is often used to map numerical weather prediction forecasts to e.g. PV power or to reduce systematic bias in forecasts.
- A common way to issue probabilistic forecasts is by quantile regression, such that $q_\tau = F^{-1}(\tau)$ is the τ^{th} quantile forecast and F^{-1} an inverse cumulative distribution function (CDF).
- By choosing e.g. $\tau = [0.10, 0.30, \dots, 0.90]$ it is possible to issue a predictive discrete inverse CDF:

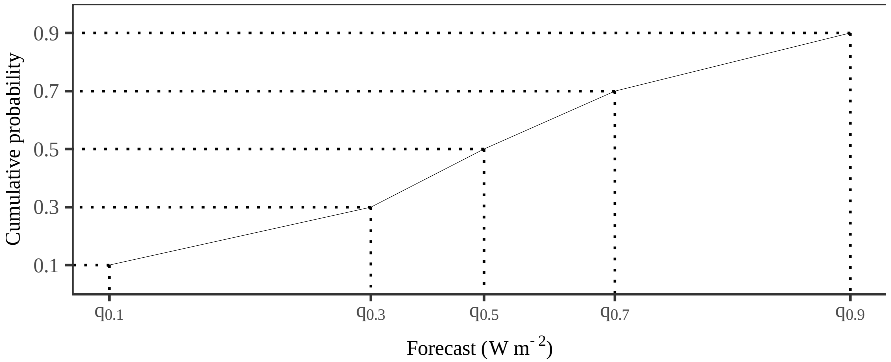


Figure: Example of a predictive discrete inverse CDF.

Space-time trajectories from probabilistic forecasts

- Drawing a random number u from $U[0,1]$ and interpolating, it is possible to generate a value from the discrete inverse CDF:

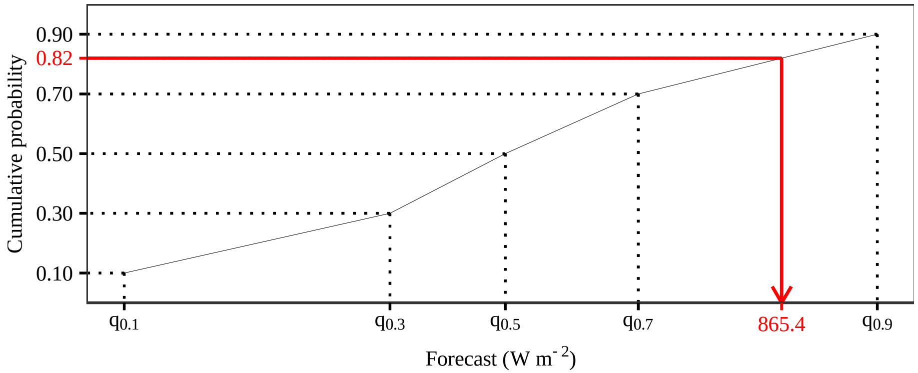


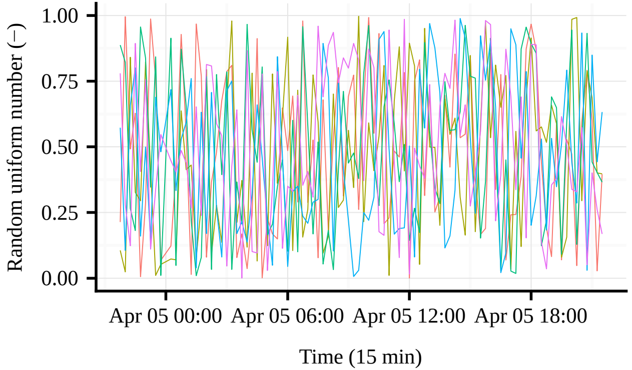
Figure: Generating a value from the discrete inverse CDF using a random number (0.82) and linear interpolation.

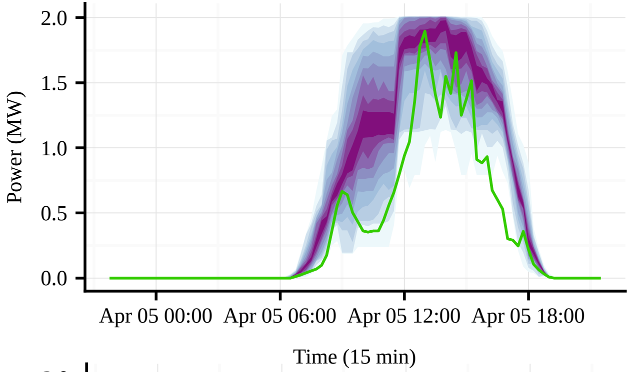
- This is known as the inverse probability integral transform: $x = F^{-1}(u)$.
- When probabilistic forecasts are issued for $z = 1, \ldots, Z$ locations and $k = 1, \ldots, K$ horizons, $D = Z \times K$ random numbers are required to generate 1 space-time trajectory.

Space-time trajectories from probabilistic forecasts

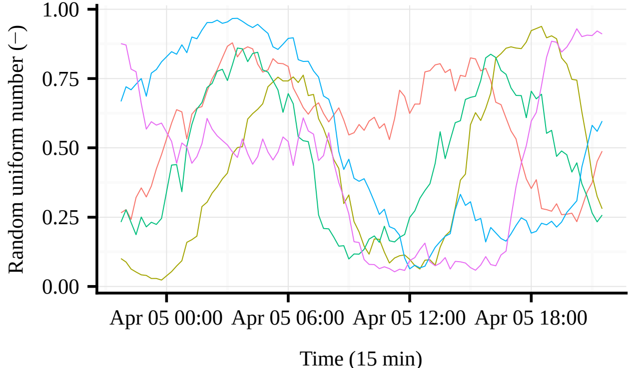
It is important that the uniform random numbers accurately represent the spatio-temporal correlation. Consider the purely temporal example ($5 \times K$):

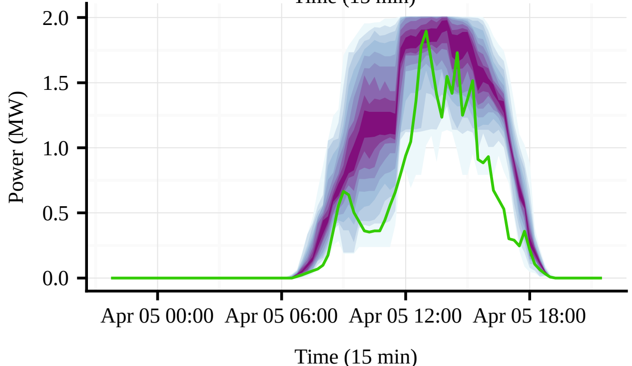
Random





Autocorrelation





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Space-time trajectories from probabilistic forecasts

- We compare copulas to model the spatio-temporal dependence structure and sample correlated random numbers from it [2].
- Consider random variables $(X_1, \dots, X_D)$ with CDFs $F_{X_1}, \dots, F_{X_D}$.
- Sklar's theorem states that every multivariate CDF can be expressed using the marginals and a copula C: $F_{X_1,\dots,X_D}(X_1, \dots, X_D) = C\left(F_{X_1}(X_1), \dots, F_{X_D}(X_D)\right)$. [3]
- The copula can be written as: $C(u_1, \dots, u_D) = F_{X_1,\dots,X_D}\left(F_{X_1}^{-1}(u_1), \dots, F_{X_D}^{-1}(u_D)\right)$.
- Then, it is possible to sample random uniform numbers $(U_1, \dots, U_D)$ and generate space-time trajectories.

Data and approach

- Aim: compare suitable copulas for multivariate solar forecasts.

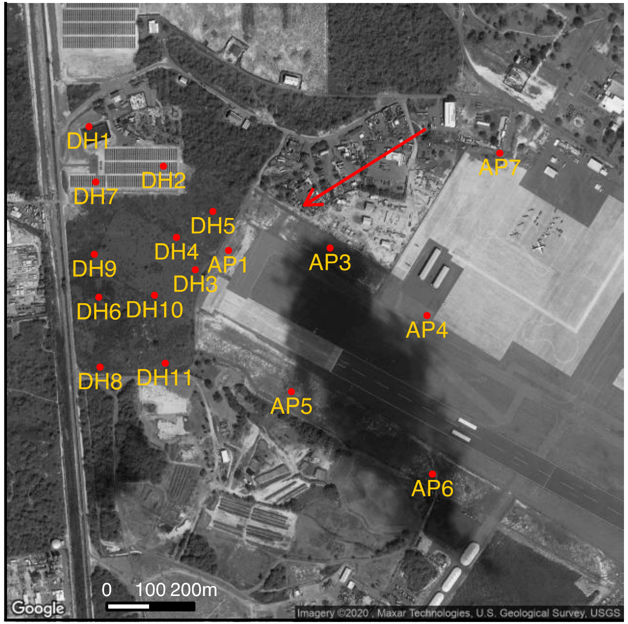

Figure: Oahu pyranometer network [4]. The red arrow indicates the prevailing wind direction. From [2].

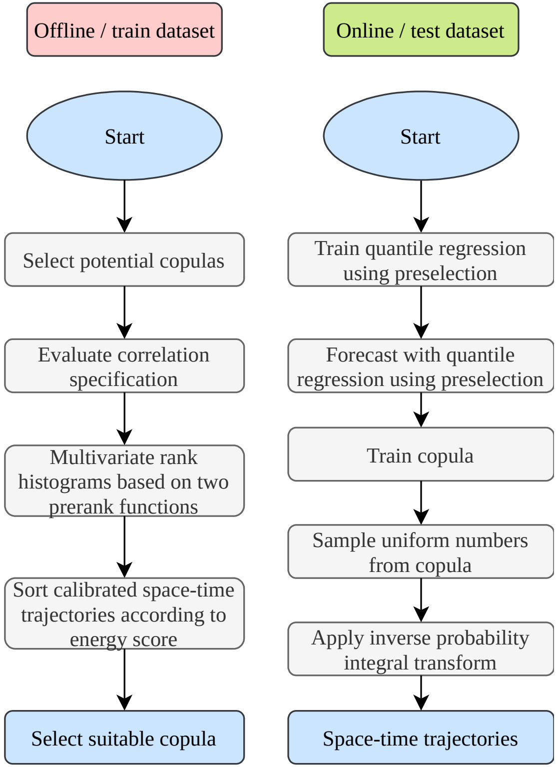

Figure: Flowchart that presents the methodology for selecting the copula (offline) and how it is used in an online setting or on the available test dataset

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Probabilistic and multivariate forecast assessment

- Probabilistic and multivariate forecasts should be calibrated for optimal decision-making processes.
- A flat rank histogram is a necessary condition for calibration, meaning that—on average—it is equiprobable for any ensemble member to predict the observation.
- Since there are D dimensions instead of 1, dedicated 'prerank' functions have been proposed that result in the average and band depth rank histograms [4].
- $\begin{pmatrix} y_1 & y_2 & \cdots & y_D \\ x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{S,1} & x_{S,2} & \cdots & x_{S,D} \end{pmatrix}$ instead of $\begin{pmatrix} y_1 \\ x_1 \\ x_2 \\ \vdots \\ x_S \end{pmatrix}$

PVPS

Results

- In this case, the Gaussian copula is not flexible enough to model the spatio-temporal dependence structure.
- The Student-*t* copula results in too high correlation or underdispersed trajectories.
- The type of miscalibration from the rank histograms for the Clayton copula is inconclusive except that calibration overall is quite poor.
- The empirical copula produced slightly underdispersed trajectories caused by the probabilistic forecasts.

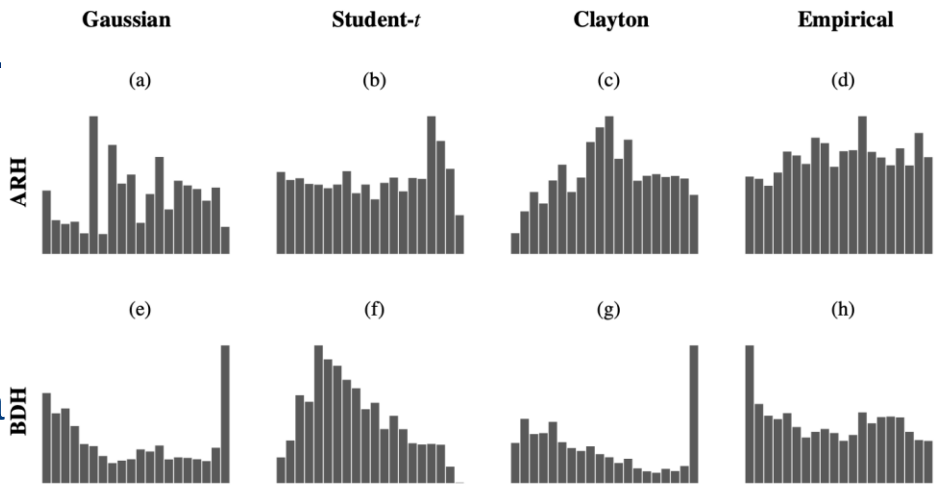

Figure: The multivariate rank histograms organized by copula (columns) and prerank function. The top row presents the average rank histogram and the bottom row represents the band depth rank histogram [2].

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Conclusions

- Space-time trajectories are an important input to decision-making processes where the spatio-temporal relationship contains valuable information.
- Space-time trajectories can be created through several techniques but we focused on probabilistic forecasts and copulas.
- A copula is a versatile tool that allows modeling the dependence structure and marginal distributions separately.
- We found that the parametric copulas (Gaussian, Student-*t* and Clayton) are in this case not flexible enough for the relatively large number of dimensions.
- The empirical copula showed better performance, which is probably because it is nonparametric.

Thank you for your attention

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References

[1] P. Pinson, "Wind Energy: Forecasting Challenges for Its Operational Management," Stat. Sci., vol. 28, no. 4, pp. 564–585, 2013.

[2] D. van der Meer, D. Yang, J. Widén, and J. Munkhammar, "Clear-sky index space-time trajectories from probabilistic solar forecasts: Comparing promising copulas," J. Renewable Sustainable Energy 12, 026102 (2020).

[3] R. B. Nelsen, An Introduction to Copulas, Springer Series in Statistics (Springer-Verlag, Berlin, Heidelberg, 2006).

[4] M. Sengupta and A. Andreas, "Oahu solar measurement grid (1-year archive): 1-second solar irradiance; oahu, hawaii (data)," 2010. Data retrieved from: https://midcdmz.nrel.gov/oahu_archive/.