Wind Turbine Performance Assessment & Power Curve Outlier Rejection Using Copula Modelling

Giorgio Zorzi, Bruce Stephen, David McMillan
Institute for Energy and Environment, Department of Electronic and Electrical Engineering,
University of Strathclyde, Glasgow G1 1RD, UK
giorgio.zorzi@strath.ac.uk

University of Strathclyde Engineering

Abstracts

The conventional means of assessing performance of a wind turbine is through consideration of its power curve. However, this representation fails to capture plausibility of measurement and cannot provide anomaly detection capabilities, which may assist in the detection of plant degradation. Although the probabilistic form of the power curve is complex, Copula models are presented here as a means of expressing the operational power curve as a joint distribution of wind speed and power output. This probabilistic model is demonstrated as an efficient way to remove outliers from operational SCADA data, simplifying and accelerating the process of identifying plant maloperation.

Objectives

Creating a Generative Model from the joint probability density of the active power and wind speed has several useful applications in condition monitoring:

- **Anomaly detection**: How likely is an observation pair? is the average likelihood deteriorating? Does this related to an incipient problem? (performance degradation, leading edge erosion etc)
- **Prognostics/model comparison**: Is the model changing over time? How does it compare with other turbines? (see Fig. 1) Formal model comparison methods can look at similarity between distributions and could 'recommend' plant with similar characteristics that has failed previously.

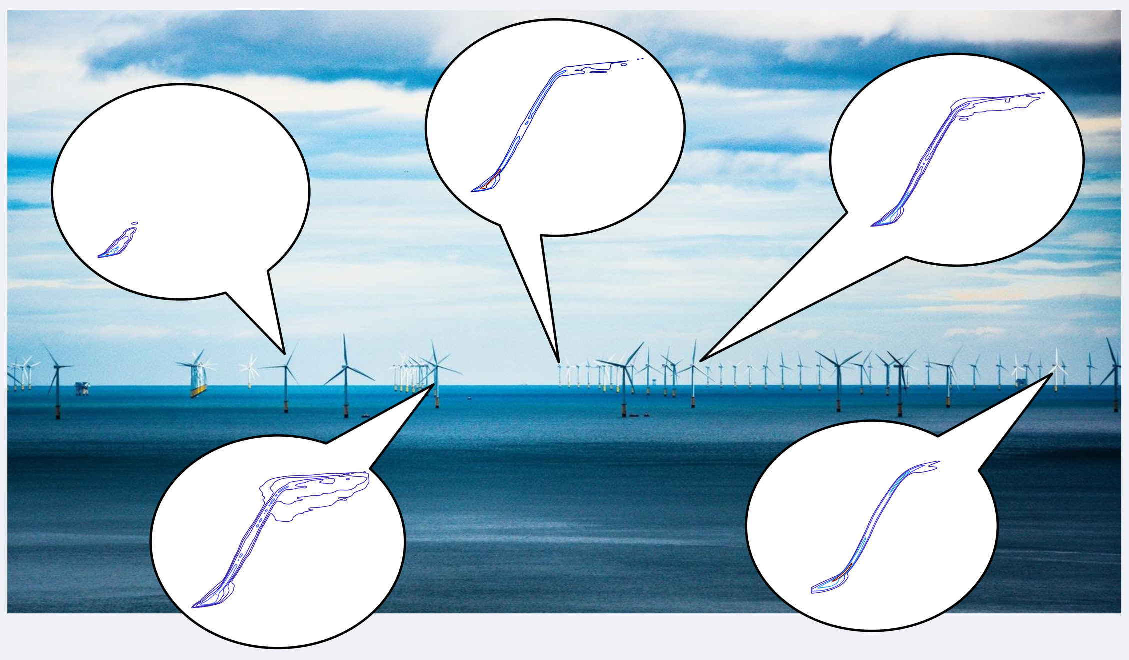

Fig. 1: Comparison of fitted copulas for different turbines

- **Diagnostics**: has a feature of the curve changed? What does this mean in terms of plant condition? How do these change between plant and over time? Does this correspond to degradation? (see Fig. 2)

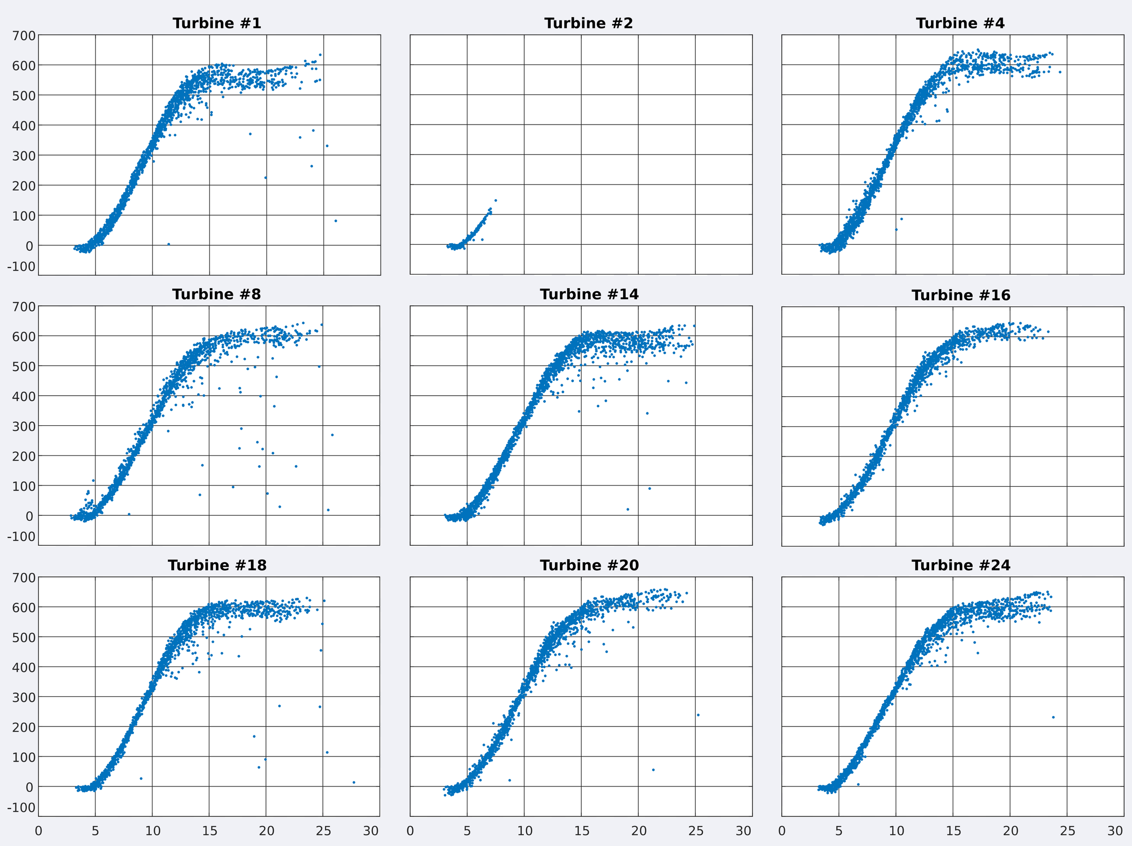

Fig. 2: Change in power curve for different turbines

Methods

Originating from Sklar's Theorem [1], Copulas are a way of describing how to relate marginal densities to joint densities with a complex dependency structure specified in a single function.

A d-dimensional joint probability density function can be expressed as a function of the marginal distributions $F_i(x_i)$, and a Copula function C that express the relationship between wind speed and power.

Copulas only works on Uniform marginals, so x_i are transformed using their respective CDFs $F_i(x_i)$ (see Fig. 3).

Several Copula families have been described in the literature, which all possess different characteristics as can be observed in Fig. 4.

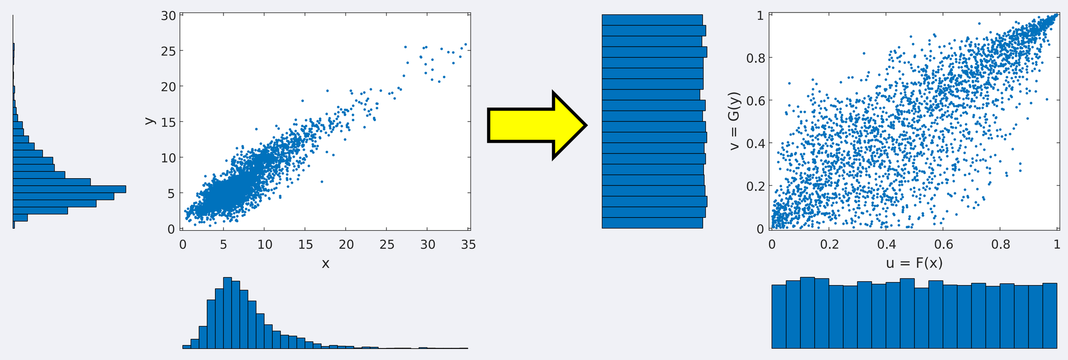

Fig. 3: From the original variables to the transformed space with uniform marginals

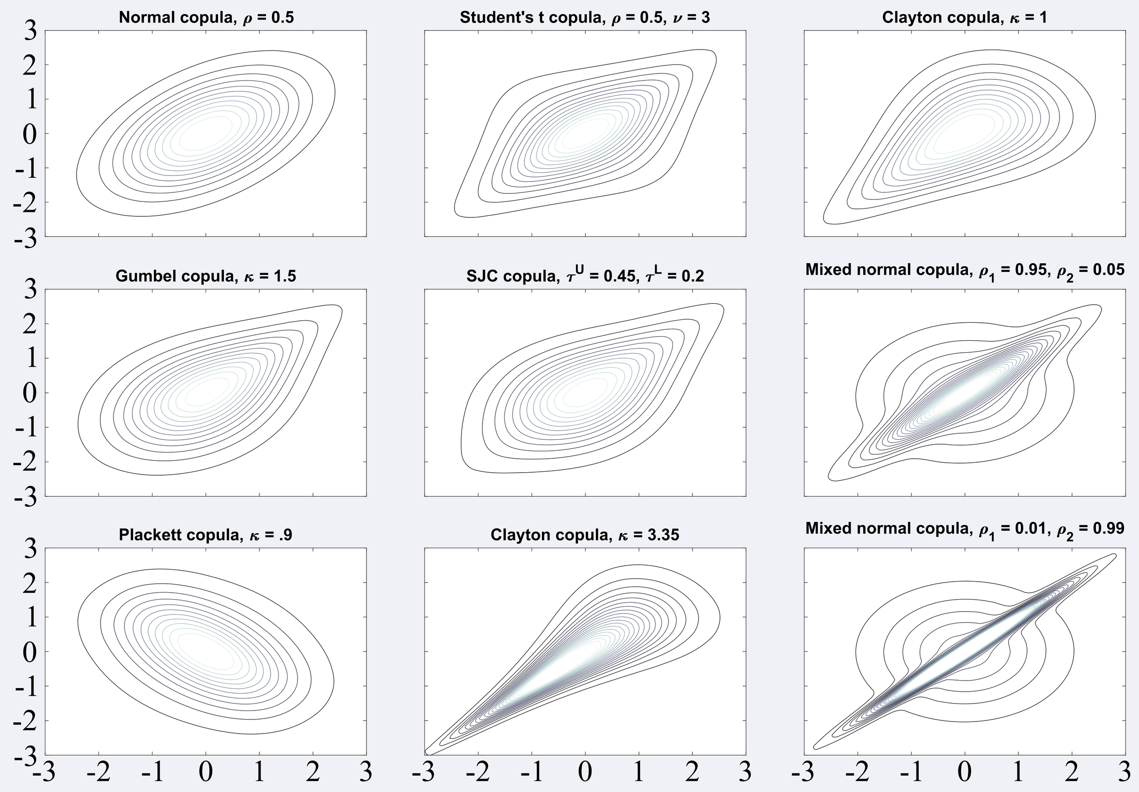

Fig. 4: Different Copulas showing different tail dependence

Considering the multiple modes of the of the wind turbine power curve, a Gaussian copula would not be a good fit. Gaussian Mixture Copula (GMC) [9] on the other hand is able to represent a more complex dependence structure using a Gaussian Mixture Model (GMM). The GMC has the following form

$$c_{gmc}(u_1, u_2, \ldots u_d, \Theta) = \frac{\psi(y_1, y_2, \ldots y_d, \Theta)}{\prod_{j=1}^{d} \psi_j(y_j)}$$

where ψ is the GMM with M number of modes as follows

$$\psi(x_1, x_2, \ldots x_d, \Theta) = \sum_{k=1}^{M} \alpha^{(k)} \phi(x_1, x_2, \ldots x_d, \theta^{(k)})$$

And y_j denotes the inverse distribution function of the GMM on the j^{th} dimension.

Results

In previous works in the field of wind turbine condition monitoring, the joint probability density of wind speed and active power has been hypothesised to be an indicator of various classes of plant faults and demonstrated to be able to detect some at their onset [5]. Additionally, Copulas have been shown to be able to manipulate the form of some marginal distributions into the shape of the power curve [3]. Rather than make assumptions of the form of the marginal distributions and the functional form of the Copula, it is proposed these are obtained from historical operational data [7].

In order to fit a Copula to the data, the SCADA data needs firstly to be pre-processed. The outliers are removed looking at the relationship between the different variables in the SCADA data, similarly to what has been done in [8].

The number of modes for the Gaussian mixture copula model is then derived from the number of operational modes in a wind turbine; below cut-in, below rated and above rated (see Fig. 5).

Once identified the number of modes, a GMCM can be fit to the data.

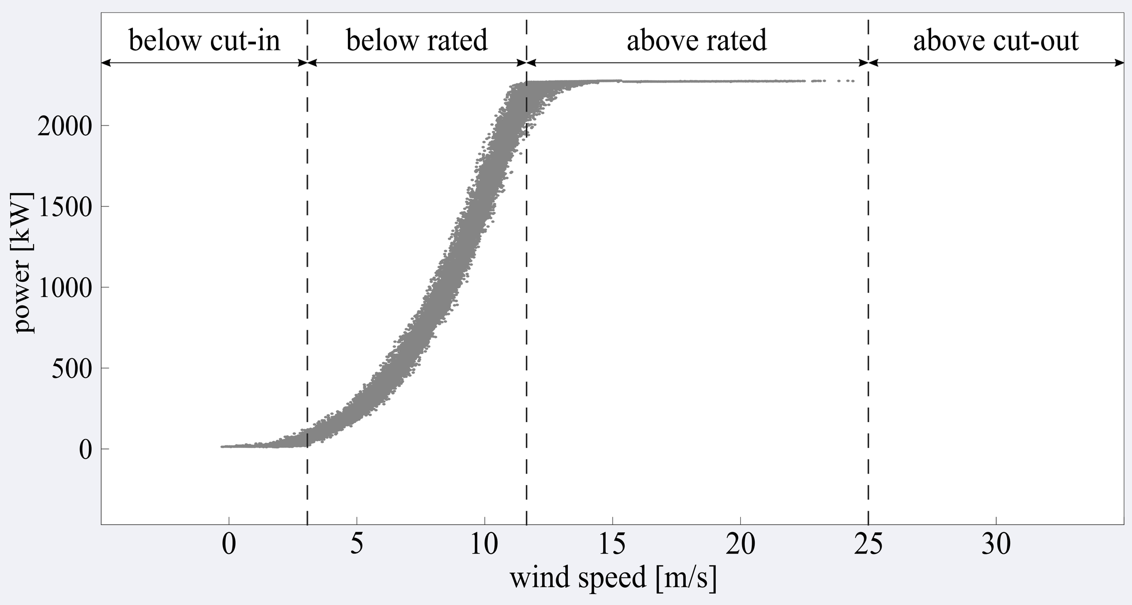

Fig. 5: Wind turbine operating regimes

Fig. 6 shows the result of this process where the joint probability illustrate the probability in the wind speed-power space. In the same figure can also be observed the marginal for wind speed and power which have been obtained using a kernel density estimator with the advantage of not following any parametric probability distribution.

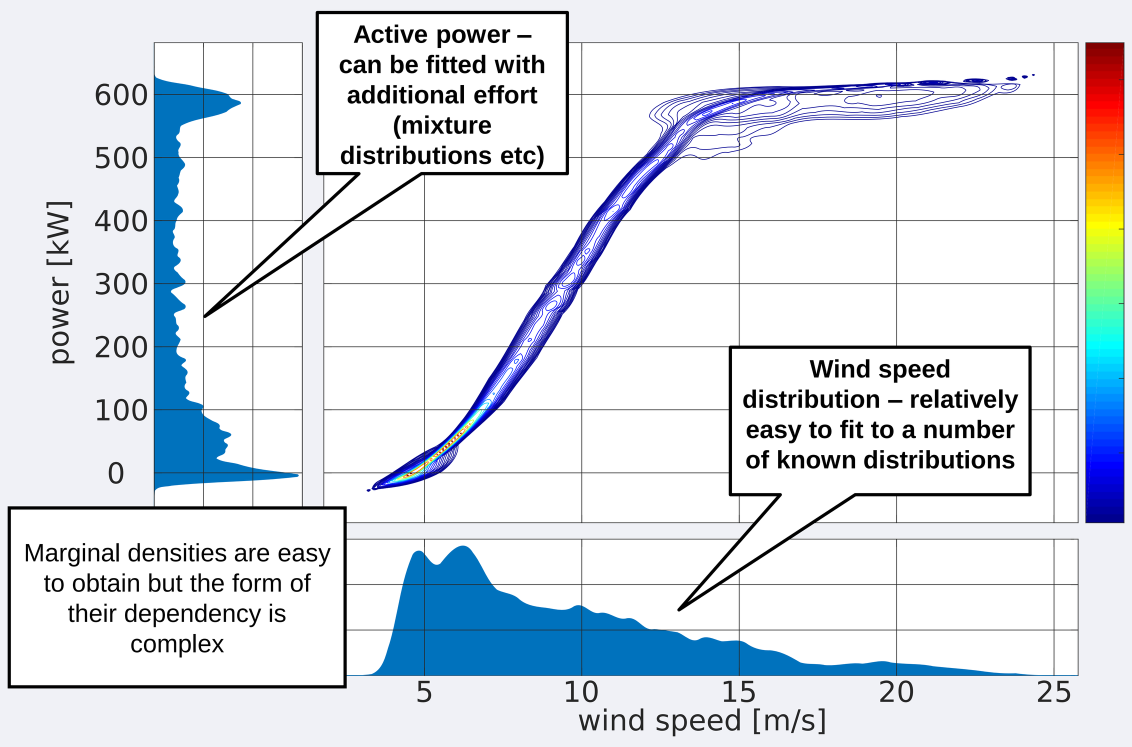

Fig. 6: Joint probability in the wind speed – power space given by the fitted GMCM, and relative marginal.

Similarly to [4], the probabilistic power curve can also be used as a tool for outliers rejection. This can be implemented simply removing the points which possess a probability lower than a pre-defined tolerance. The result of this procedure can be seen in Fig. 7, where the red dots are the rejected points. In particular can be observed the effect of the choice of the contour level on the final result.

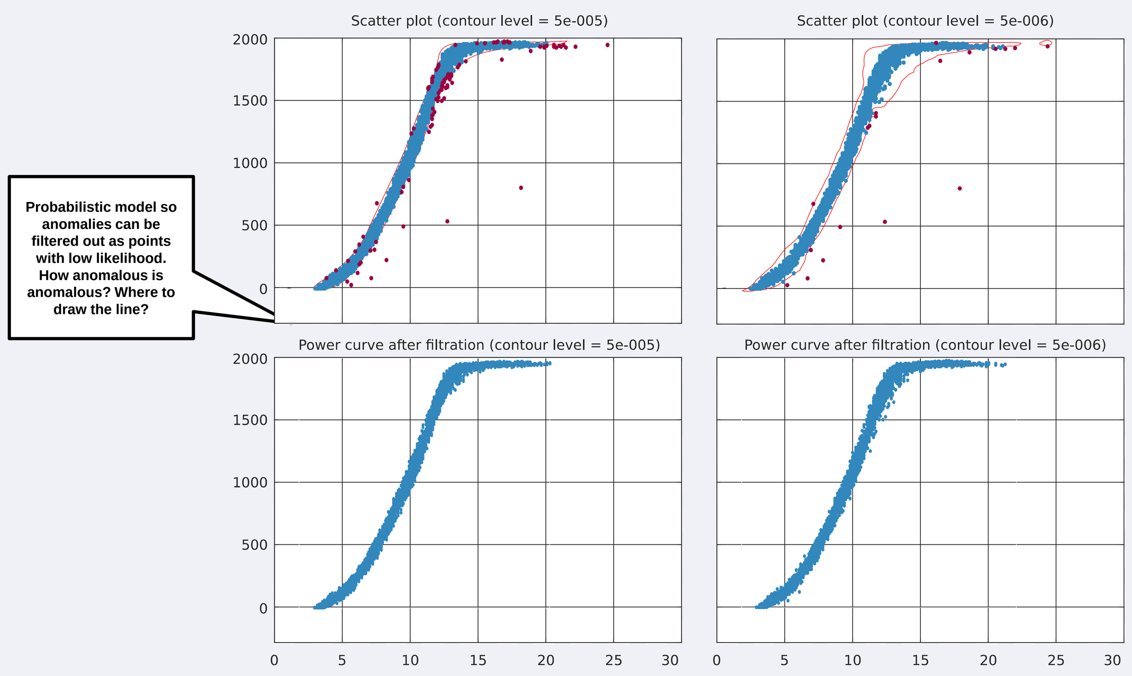

Fig. 7: Joint probability in the wind speed – power space given by the fitted GMCM, and relative marginal.

Conclusions

This work has looked at creating probabilistic formulations of wind turbine power curves. Owing to the challenges faced in modelling the complex relation between wind and power produced a Copula based approach has been used to flexibly model this based on operational data. The resulting model has a number of useful applications:

- Automatic screening of SCADA data for unrepresentative data points
- Automatic comparison and detection of performance degradation

As a formal means of probabilistic representation, the Copula approach allows the integration of additional variables such as air density and pitch and yaw angles allowing more expressive means of capturing plant performance to be developed to identify degradation onset to be captured earlier.

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