Better prediction models for renewables by training with entropy concepts

V. Miranda, *Fellow, IEEE*, C. Cerqueira and C. Monteiro

Abstract **– Prediction models for generation from renewables are needed in the context of a power system with a diversified portfolio. The presentation will discuss a new criterion and procedure to develop prediction models based on Renyi's Entropy combined with Parzen windows (an approach named Information Theoretic Learning) that is applied to wind prediction and suggested as a better training paradigm for fuzzy or neural systems.**

Index Terms **– Entropy, wind power, prediction, forecasting**

I. Introduction

In the EU, renewables assume a new role in power systems, due to the Kyoto protocol and the need to reduce dependency from oil. The penetration of wind power will be in an order of magnitude not imagined years ago. This effect is combined with the growing importance of distributed generation, also from renewable energy like mini-hydros or photo-voltaics, but also from co-generation in industry and in commerce, services and residential buildings. Robust prediction models will be needed especially for wind generation. The accuracy of generation prediction from renewables has a direct impact in electricity markets and in the market clearing prices.

Traditionally, prediction models have been tuned to satisfy a variance criterion MSE – Mean Square Error criterion. This assumes that the distribution of prediction errors is Gaussian with zero mean (the Gaussian distribution is the only one that has all information in its first two moments, mean and variance). However, this assumption is hardly ever verified.

Wind power is particularly difficult to predict. Therefore, it is of the utmost importance that all information is extracted from data instead of leaving it in the error distribution. This paper will defend that the quality of a prediction series must be measured in terms of Entropy and not of MSE. These concepts have been developed as Information Theoretic Learning [1,2].

Quadratic Renyi's Entropy is defined for a continuous random variable Y with pdf $f_Y(z)$ as

$$H_{R2} = -\log \int_{-\infty}^{+\infty} f_Y{}^2(z)dz$$

The estimation of the pdf of data from a sample constituted by discrete points $\mathbf{y}_i \in R^M$, i = 1,…,N in a M-dimensional space may be done by the Parzen window method [3]. If a Gaussian kernel is used centered on each point, the expression of the estimation $\hat{f}_Y$ for the real pdf f_Y of a set of N points is a summation of individual contributions

$$\hat{f}_Y(\mathbf{z}) = \frac{1}{N}\sum_{i=1}^{N} G(\mathbf{z}-\mathbf{y}_i, \sigma^2\mathbf{I})$$

where G(.,.) is the Gaussian kernel and $\sigma^2\mathbf{I}$ is the covariance matrix.

The presentation will show how combining these concepts one may have training algorithms that minimize H_{R2}. A neural system trained with this guiding criterion will display a better error distribution than when trained under MSE, with a higher density of zero or close-to-zero errors – see the figure below, comparing the pdf of error distribution for the two cases in an example for wind power prediction. Examples based on real data from European wind parks will be presented.

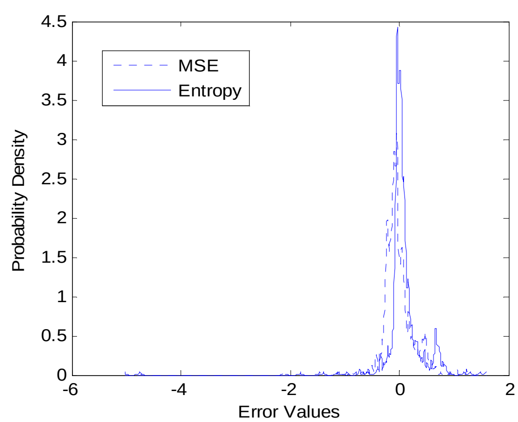

Figure 1 – Comparing error density functions for wind power predictions trained with MSE and with Entropy criteria (example from real data).

II. Acknowledgment

Work partially financed by FCT, Portugal, POSC/EEA-ESE/60980/2004.

III. References

[1] J. C. Principe and Dongxin Xu, "Introduction to information theoretic learning", *Proc. International Joint Conference on Neural Networks (IJCNN'99)*, Washington DC, USA, 10-16 July 1999, pp. 1783-1787

[2] D. Erdogmus and J. C. Principe, "Generalized Information Potential Criterion for Adaptive System Training", *IEEE Transactions on Neural Networks*, vol. 13, no. 5, September 2002, pp. 1035-1044

[3] E. Parzen, "On the estimation of a probability density function and the mode", *Annals Math. Statistics*, v. 33, 1962, p. 1065

Vladimiro Miranda is with INESC Porto and also with FEUP, Faculty of Engineering of the University of Porto, Portugal (e-mail: vmiranda@inescporto.pt).

Cristina Cerqueira is with INESC Porto and also with FCUP, Faculty of Sciences of the University of Porto, Portugal (email: caac@inescporto.pt).

Claudio Monteiro is is with INESC Porto and also with FEUP (email: cmonteiro@inescporto.pt)