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***Abstract*— As global solar radiation forecasting is a very important challenge, several methods are devoted to this goal with different levels of accuracy and confidence. In this study we propose to better understand how the uncertainty is propagated in the context of global radiation time series forecasting using machine learning. Indeed we propose to decompose the error considering four kinds of uncertainties: the error due to the measurement, the variability of time series, the machine learning uncertainty and the error related to the horizon. All these components of the error allow to determinate a global uncertainty generating a prediction bands related to the prediction efficiency. We also have defined a reliability index which could be very interesting for the grid manager in order to estimate the validity of predictions. We have experimented this method on a multilayer perceptron which is a popular machine learning technique. We have shown that the global error and its components are essentials to quantify in order to estimate the reliability of the model outputs. The described method has been successfully applied to four meteorological stations in Mediterranean area.**

Incertainty;time series;confidence bands;prediction interval

I. INTRODUCTION

Solar radiation is one of the principal energy sources for physical, biological and chemical processes, occupying the most important role in many engineering applications[1]. The process of converting sunlight to electricity without combustion allows to create power without pollution. The major problem of such energy source is its intermittence and its stochastic character which make difficult their management into an electrical network[2]; Thereby, the development of forecasting models is necessary to use ideally this technology. By considering their effectiveness, it will be possible for example to identify the most optimal locations for developing a solar power project or to maintain the grid stability and security of a power management system[3]. Thus the solar energy forecasting is a process used to predict the amount of solar energy available for various time horizons[4]. Several methods have been developed by experts around the world and the mathematical formalism of Times Series (TS) has been often used for the short term forecasting (among 6 hours ahead)[5]. TS is a set of ordered numbers that measures some activities over time. It is the historical record of global horizontal irradiance with measurements taken at equally spaced intervals with a consistency in the activity and the method of measurement. Some of the best predictors found in literature are Autoregressive and moving average, Bayesian inferences, Markov chains, k-Nearest-Neighbors predictors, support vector machine, regression tree, or artificial neural network (ANN). All these approaches are related to the machine learning application. The most often used is the last presented method: the artificial neural network and particularly the multilayer perceptron (MLP)[6]. In the present study, we focus on this prediction method, the goal being to detail the uncertainties related to the global radiation prediction. These uncertainties can be decomposed into several components that will be explained and developed.

II. DATA

In Corsica Island, the data used to build the models are GHI measured in the meteorological stations of Ajaccio (41°55'N, 8°44'E, 4m asl) and Bastia (42°42'N, 9°27'E, 10m asl). They are located near the Mediterranean Sea and nearby mountains (1000 m altitude at 40 km from the sites). The data representing the global horizontal solar radiation were measured on an hourly basis from 1998 to 1999 (exactly two years). The two last studied stations are Montpellier (43.6°N and 3.9°E, 2 m asl) and Marseille (43.4°N and 5.2°E, 5 m asl) concerning the years 2008 and 2009. All these stations are equipped with pyranometers (CM 11 from Kipp & Zonen). The choice of these particular places is explained by their closed geographical and orographical configurations. These stations are located near the Mediterranean Sea and mountains. This specific geographical configuration of the four French meteorological stations makes cloudness difficult to forecast. Mediterranean climate is characterized by hot summers with abundant sunshine and mild, dry and clear winters. Irradiance nighttime values are not being used, the first morning data forecast are operated with the day before evening data

III. PREDICTION METHODOLOGY AND ERROR DECOMPOSITION

We chose to develop error propagation in the GHI prediction for the most common used predictor: the MLP. The base of this model is the time series approach (TS). A TS $x(t)$ can be defined by a linear or non-linear model called fn (see Equation 1 where $t = n, n-1,\ldots, p+1, p$ with n, the number of observations and p the number of parameters of the model ; $n \gg p$; h is the horizon of prediction and $\epsilon\_(t+h)$ the committed error)[1].

$$x(t+h)=fn\ (x(t),x(t-1)\ldots,x(t-p+1))+\epsilon(t+h) \qquad \text{Eq 1}$$

To estimate the fn model, a stationarity hypothesis is often necessary. This condition usually implies a stable process[7]. This notion is directly linked to the fact that whether certain feature such as mean or variance change over time or remain constant. Previous studies[8–11] show that the use of clear sky index (CSI) allows to make stationary the time series and so to correctly use the MLP forecasting.

A. Stationary process

In previous studies[1,12], it was demonstrated that the clear sky index calculated with the simplified Solis model[13] is the most reliable for our locations. The Solis model generates a clear sky hourly irradiation (CS) expressed by Eq. (2), the use of this model requires fitting parameter (g), extraterrestrial radiation (I0), solar elevation (h) and total measured atmospheric optical depth (τ):

$$CS(t) = I_0\ (t).exp\left(\frac{-\tau}{sin^g(h(t))}\right).sin(h(t)) \qquad \text{Eq 2}$$

The simplified "Solis clear sky" model is based on radiative transfer calculations and the Lambert-Beer relation[14]. The expression of the atmospheric transmittance is valid with polychromatic radiations, however when dealing with global radiation, the Lambert-Beer relation is only an approximation because of the back scattered effects. According to [1] this model remains a good fitting function of the global horizontal radiation. The new computed time series (CSI) can be directly used with the MLP forecasting and is described be the equation 3:

CSI(t)=GHI(t)/CS(t) Eq 3

B. MLP prediction

Although a large range of different architectures of ANN is available[9], MultiLayer Perceptron (MLP) remains the most popular [35]. In particular, feed-forward MLP networks with two layers (one hidden layer and one output layer) are often used for modeling and forecasting time series. Several studies[15] validated this approach based on ANN for the non-linear modeling of time series. To forecast the time series, a fixed number p of past values are set as inputs of the MLP, the output is the prediction of a future value[16]. Considering the initial time series equation (Equation 1), this equation can be adapted to the non-linear case of one hidden layer MLP with b related to the biases, f and g to the activation function of the output and hidden layer, and ω to the weights. The number of hidden nodes (H) and the number of the input node (In) allow to detail this transformation. The number of layer 1 and 2 is given in superscript. (Equation 4):

$$\widehat{CSI}(t+1) = f(\textstyle\sum_{i=1}^{H} y_i\, \omega_i^2 + b^2)\ with$$

$$y_i = g(\textstyle\sum_{j=1}^{In} CSI(t-j+1)\, \omega_{ij}^1 + b_i^1) \qquad \text{Eq4}$$

In the presented study, the MLP has been computed with the Matlab© software and its Neural Network toolbox. The characteristics chosen and related to previous work are the following: one hidden layer, the activation functions are the continuously and differentiable hyperbolic tangent (hidden) and linear (output), the Levenberg-Marquardt learning algorithm with a max fail parameter before stopping training equal to 5. This algorithm is an approximation to the Newton's method. The prediction of the GHI is obtained using the equation:

(GHI)̂(t+1)=(CSI)̂(t+1).CS(t+1) Eq 5

To customize the input layer of the MLP we choose the use of the mutual information to determine In as described in[1,17–20]. According the results obtained in these papers, we use H equal to In for all the experiments conducted in this study. Furthermore in order improve the learning of the MLP, it is a common practice to filter out the data removing night hours. Indeed we consider only periods between sunrise and sunset [41,42]. We have chosen to apply a selection criterion based on the solar zenith angle (SZA): solar radiation data for which the solar zenith angle is greater than 80° have been removed[1]. This transformation is equivalent to a filtering related to the solar elevation angle lower than 20.

C. Error decomposition

In these section, we propose to decompose the error considering four kinds of uncertainties: the error due to the measurement, the error due to the variability of the time series, the error related to the machine learning uncertainty and the error related to the horizon.

In our assumption, all the previous σ terms are independent random variables that are normally distributed (and therefore also jointly so), then their sum is also normally distributed and the global form of the standard deviation $\sigma_{tot}(t+1)$ becomes (in this equation the quick fluctuations are taken into account with σ_{var}, but it is also possible to consider σ_{inh}):

$$\sigma_{tot}(t+1) = \sqrt{(\sigma_{meas})^2 + \left(\sigma_{samp}(t+1)\right)^2 + (\sigma_{ini}(t+1))^2 + (\sigma_{var}(t+1))^2} \qquad \text{Eq 6}$$

Considering that there is a persistence of the variability for a short horizon, $\sigma_{var}(t) = \sigma_{var}(t+1)$

thus:

$$\sigma_{tot}(t+1) = \sqrt{(\sigma_{meas})^2 + \left(\sigma_{samp}(t+1)\right)^2 + (\sigma_{ini}(t+1))^2 + (\sigma_{var}(t))^2} \qquad \text{Eq 7}$$

With $\sigma_{meas} = \sigma(CSI)\left(\sum_{j=1}^{Ne}(\sum_{i=1}^{Nc}\omega_i^2\omega_{ij}^1)^2\right)^{1/2}$, σ_{samp} and σ_{ini} are computed respectively with k-fold and 50 random initializations and $\sigma_{var} = \widehat{GHI}(t+1).g\big(Vol2(t)\big)$. For an easier computing, it is also possible to use σ_{inh} replacing $\sigma_{var}(t)$ with a less robust result but not dependent on the instant of the prediction.

$$\sigma_{tot}(t+1) = \sqrt{(\sigma_{meas})^2 + \left(\sigma_{samp}(t+1)\right)^2 + (\sigma_{ini}(t+1))^2 + (\sigma_{inh})^2} \qquad \text{Eq 8}$$

It is possible to define a prediction band taking into account all the uncertainties (Eq 9).

$$\widehat{GHI}(t+1) = \widehat{GHI}_{MLP}(t+1) \pm \sigma_{tot}(t+1) \qquad \text{Eq 9}$$

Such prediction intervals were often proposed in the literature [21–23]; they refer to machine learning method $(\sigma_{ML}(t+1))^2 = \left(\sigma_{samp}(t+1)\right)^2 + (\sigma_{ini}(t+1))^2$ [21,23] or to volatility and $\sigma_{var}(t)$ [22] but rarely both to the two kinds of uncertainty and never concerning σ_{meas}. Note that in the case of other machine learning method used the term σ_{ini} can be equal to zero (e.g. support vector regression, regression tree etc.). The ideal case would be to systematically propose a confidence interval of prediction related to the three sorts of uncertainty (with $\sigma_{TS} = \sigma_{var}(t)\ or\ \sigma_{inh}$ considering the desired reliability).

$$\sigma_{tot}(t+1) = \sqrt{(\sigma_{meas})^2 + (\sigma_{ML}(t+1))^2 + (\sigma_{TS}(t))^2} \quad \text{Eq 10}$$

Now, considering the horizon of prediction, we define the new global uncertainty with the equation 30 with $\sigma_{hor} = \widehat{GHI}(t+h).\alpha(h)$.

$$\sigma_{tot}(t+h) = \sqrt{(\sigma_{meas})^2 + (\sigma_{ML}(t+1))^2 + (\sigma_{TS})^2 + (\sigma_{hor}(h))^2} \quad \text{Eq 11}$$

IV. RESULTS

The previous components allows to calculate the global uncertainty and to propose two prediction bands: UB for upper band and LB lower band [24]. Thus, the quality of the prediction can be defined by the triplet $\{\widehat{GHI}(t+h); LB; UB\}$ [25]. We can also estimate the reliability of the prediction considering that the prediction is efficient when UB-LB is very lower than $\widehat{GHI}(t+h)$ and inefficient when UB-LB is equal or upper to $\widehat{GHI}(t+h)$ value. From this hypothesis, we can define the reliability η as η(t+1)=1– (UB(t+1)-LB(t+1))/$\widehat{GHI}(t+h)$. Lower is this parameter, more efficient is the prediction. We construct a reliability index between 0 and 1 considering that if (UB(t+1)-LB(t+1))/$\widehat{GHI}(t+h) > 1$, then η(t+1)=0 , i.e. the prediction is not sure. The final prediction becomes:

-$\widehat{GHI}(t+h) = \langle\widehat{GHI}(t+h)\rangle$, average of 50 simulations (50 training and initialization weights, 50 different training sets)

LB=

$$\sqrt{(\sigma_{meas})^2 + \left(\widehat{GHI}_{min}(t+h) - \langle\widehat{GHI}(t+h)\rangle\right)^2 + (\sigma_{inh})^2 + (\sigma_{ho}}$$

Eq 34

UB=

$$\sqrt{(\sigma_{meas})^2 + \left(\widehat{GHI}_{max}(t+h) - \langle\widehat{GHI}(t+h)\rangle\right)^2 + (\sigma_{inh})^2 + (\sigma_{hor}(h))^2}$$

Eq 35

With $\sigma_{meas}\left(\widehat{GHI}(t+1)\right) = 1\%.\widehat{GHI}(t+1)$, $\sigma_{inh} = \widehat{GHI}(t+1).nRMSE(GHI_{trend}(t) - GHI(t))$, $\sigma_{hor}(h) == \widehat{GHI}(t+h).\alpha(h)$ and $\widehat{GHI}_{min/max}(t+h)$ are the min and max values of the 50 predictions generated with 50 simulations. The figure 5 shows for Ajaccio an example of the prediction bands, considering all the kind of uncertainty with horizon h=1 hour. Line represents measurement and dashed lines the upper and lower bands concerning each kind of uncertainties.

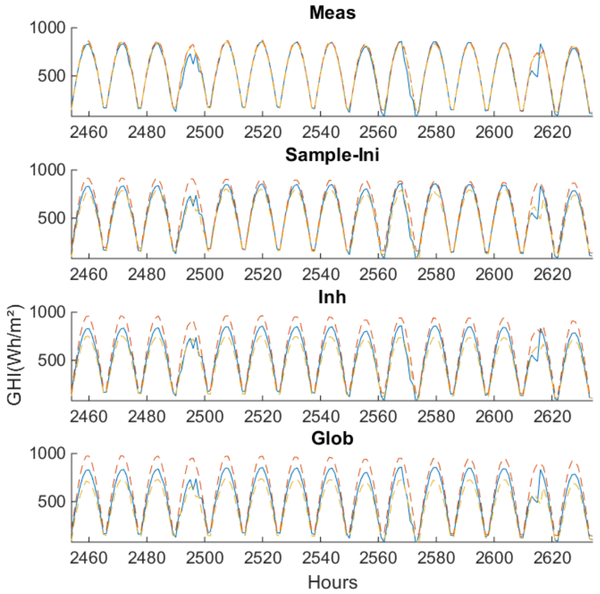

Figure 1. Uncertainty in the GHI predictions for the horizon h=1 for Ajaccio case

We can see that σ_{meas} is the parameter the less interesting for the bands construction and that it is necessary to consider the coupling of σ_{inh} and σ_{ML} (related to $\sigma_{samp}\ and\ \sigma_{ini}$) for a good prediction interval definition. For other sites the obtained curve are similar and no more information is observed. In the figure 6, the top curve (same prediction configuration that previously) compared the average prediction $\widehat{GHI}(t+h)$ (marks) versus the GHI measurement (line). The bottom curve shows the associated reliability index (η(t+1)).

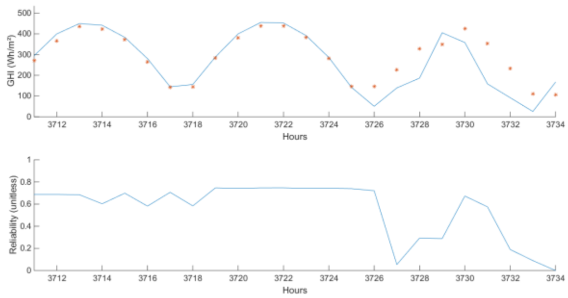

Figure 2. Comparison for the horizon h=1 for Ajaccio of GHI predictions (mark) and GHI measurement (line) on the top and associated reliability index in the bottom

We see that when the variability is low (two first day from 3711 to 3726) the reliability is important (close to 70%) but when cloud occurs the value is much lower and can reach 0%..

V. CONCLUSIONS

In this paper we have shown that it is possible to compute a prediction band in the context of global radiation time series forecasting using machine learning. We have define for a popular machine learning technique, the multilayer perceptron, four kinds of uncertainties: the error due to the measurement, the variability of time series, the machine learning uncertainty (initialization and sampling) and the error related to the horizon. In literature, rarely both to the two kinds of uncertainty σ_{ini} and σ_{ML} are studied, and never σ_{meas}. We have also defined a reliability index which could be very interesting for the grid manager in order to estimate the validity of predictions. The described method has been successfully applied to five meteorological stations in Mediterranean area. We are sure that it is possible to generalize the approach to other sites and other machine learning tools. Thereby in future, we will try to apply the methodology to other time granularities and predictor as SVM, regression tree or random forest.

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