Kalman filtering and classical time series tools for global radiation prediction

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1. Introduction

For nowcasting and short term forecasting of salar irradiation, the usual technics are based on machine learning predictions such as Artificial Neural Network (ANN) [1], Support Vector Machines (SVM) [2], AutoRegressive–Moving-Average (ARMA) models [3], etc. A significant inconvenience of these methods is related to the large historic data set required during the training phase of the predictors; thus, in this work, we propose a simple methodology able to predict a global radiation time series without the need of historical data, making the method easily applicable for poor instrumented areas. We suggest to call these intuitive methods in the following “training-less” methods. The accuracy of these methods will be compared against other classical prediction methods, taking into account the time horizon of the prediction.

2. Data

The solar data used in the models are global horizontal irradiations (GHI) measured at the meteorological station of Ajaccio (Corsica Island, France, 41°55 N, 8°44 E, 4m asl) with pyranometers (CM 11 Kipp & Zonen). Data are related to an hourly basis from 1998 to 2009 (11 complete years).

3. Models

3.1. Data driven methods

-Linear model: AutoRegressive process (**AR**). In an AR model, the future value of a variable namely $\widehat{GHI}(t+h)$ is assumed to be a linear combination of several past observations $(t-i)$. In this study, the complexity of the model depends on the autoregressive order *p* which is optimized using the auto-mutual information factor.

-Non-linear model: neural network model (**ANN**). It is the predominant method in the domain of time series forecasting. Indeed, the availability of meteorological historical data databases and the fact that ANN are data driven approaches capable of performing a non-linear mapping between sets of input and output variables make this modelling tool very attractive. In the present study, the ANN model has been computed with the Matlab© software and its Neural Network toolbox. The Levenberg-

Marquardt learning algorithm with a max fail parameter before stopping training equal to 3 was used to estimate the ANN model's parameters. The max fail parameter corresponds to a regularization tool limiting the learning steps after a characteristic number of predictions failures. Consequently it is a means to control the model complexity [4].

3.2. Training-less methods

-The persistence. This naïve method is the most cost-effective forecasting model, it provides a reference against which more sophisticated models can be compared. Using the naïve approach produced forecasts are equal to the last observed value. It simply states that future GHI values will be equal to observed GHI at time t (i.e. the atmospheric conditions and solar irradiation remain unchanged between current time t and future time *t+h*).

-Scaled persistence. Using the clear sky model (simplified solis model [5]), this training-free prediction model can be defined by:

$$\widehat{GHI}_{SP}(t+1) = GHI(t).\frac{GHI_{clsk}(t+1)}{GHI_{clsk}(t)} \quad (1)$$

-Kalman filter. It is a recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. The Kalman filter can be written as a single equation, however it is most often constructed with two distinct phases: prediction and update. The prediction phase uses the state estimated from the previous timestep (t-1) to produce an estimation of the state at the current timestep (t). This predicted state estimated is also known as the *a priori* state estimated because, although it is an estimation of the state at the current timestep, it does not include observation information from the current timestep. In the update phase, the current *a priori* prediction is combined with current observation information to refine the state estimated. This improved estimation is termed the *a posteriori* state estimated. With this methodology, the forecasting algorithm becomes [6]:

$$GHI(t+1) = A(t).GHI(t) + \omega(t) \quad (2)$$

With ω a multivariate normal distribution with covariance Q (=ℵ (0,Q)) and $A(t) = \frac{GHI_{clsk}(t+1)}{GHI_{clsk}(t)}$. At time t, an observation (or measurement) z(t) of the true state GHI(t) is made according to:

$$z(t) = H(t).GHI(t) + v(t) \quad (3)$$

Where *v* is the observation noise which is assumed to be zero mean Gaussian white noise with covariance *R* (=ℵ (0,*R*)) [7]. The initial state, and the noise vectors at each step are all assumed to be mutually independent. In our problem, the prediction defining the state vector is defined by:

$$\widehat{GHI}(t|t-1) = \widehat{GHI}(t-1|t-1).A(t-1) \quad (4)$$

$\widehat{GHI}(t|t)$ is the predicted value of GHI given the measured value of GHI at time (t). It is in fact, an *a posteriori* state estimated at time *t* given observations up to and including time *t.* Then the *a posteriori* error covariance matrix P (a measure of the estimated accuracy of the state estimated) is calculated [8].

$$P(t|t-1) = A(t-1).P(t-1|t-1).A(t-1)^T + Q \quad (5)$$

From this last equation, we define the filter gain *K* which is then computed:

$$K(t) = P(t|t-1).H(t).(H(t).P(t|t-1) + R)^{-1} \quad (6)$$

A correction factor is then introduced and defined by [9]:

$$\widehat{GHI}(t|t) = \widehat{GHI}(t|t-1) + K(t).\left(z(t) - H(t).\widehat{GHI}(t|t)\right) \quad (7)$$

$$P(t|t) = P(t|t-1) - K(t).H(t).P(t|t-1) \quad (8)$$

The prediction for the horizon 1 becomes:

$$\widehat{GHI}_{kalman}(t+1|t) = A(t).\widehat{GHI}(t|t) = \frac{GHI_{clsk}(t+1)}{GHI_{clsk}(t)}.\widehat{GHI}(t|t) \quad (9)$$

Note that the approach is easily generalizable for other horizons h ($\widehat{GHI}_{kalman}(t+h|t)$).

4. Results

This section details the main results we obtained on the previous presented models for time granularity 1 hour and for 10 horizons (t+1 to t+10). In the Table 1 are shown results of prediction for all the predictors described previously.

		Annual	Quarter 1	Quarter 2	Quarter 3	Quater 4
Data driven models	AR	0,1953	0,1722	0,2349	0,1259	0,2203
	NN	**0,1947**	0,1707	**0,2320**	0,1287	**0,2184**
Trainless models	persistence	0,3427	0,3065	0,3933	0,3092	0,3687
	Scaled persisitence	0,2022	0,1721	0,2391	**0,1186**	0,2344
Resursive trainless models	Kalman filtering	0,2010	**0,1706**	0,2391	0,1197	0,2330

Table 1. Results (nRMSE) in the hourly case of the 8 predictors among the 3 types of forecasters (models, trainless models and recursive trainless model), in bold the best results for each column.

We can see that the best predictors (in the Annual case) are AR and NN but these are also the more elaborated methods. It is essentially during the second and last quarters that errors are very large, during these seasons it is ANN and AR which give the best results. Because the prediction of the global forecasting is not only interesting 1 hour in advance, we will propose to study the impact of the considered horizon on the predictors. Figure 1 shows the nRMSE related to the horizon.

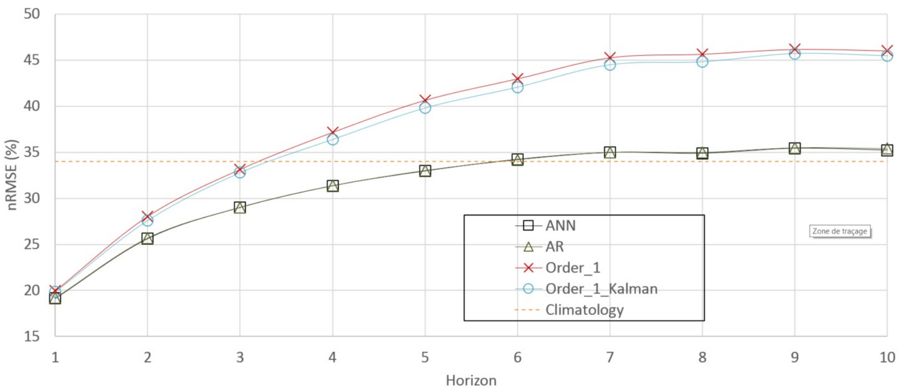

Figure 1. nRMSE evolution in term of time horizons

Previously (1 hour horizon case) we've shown that trainless model (scaled persistence and Kalman filter) were similar to NN and AR models. When horizon increases, this effect becomes false, from the 2 hours horizon, the two last one are very better than the first ones. Moreover the NWP is better than NN and AR from the 6 hours horizon and better than the order_1 and Kalman filter from the 3 hours horizon.

5. Conclusion

In the scope of satisfying electrical operator needs, several kinds of short term prediction methodologies: a naïve model, a linear model, non-linear models and models without training phase have been described. The difference of performance being very small, it is very difficult to compare all the presented predictors. All of them seem interesting to predict the global solar radiation depending on use situation: timestep, horizon, size of the training set, etc. Applying the parsimony concept, a model using the recursive Kalman method of scaled persistence is used performing the prediction from an ad-hoc filtering. The Kalman filter is a recursive estimator, this means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. In contrast to batch estimation techniques, no history of observations and/or estimates is required. Kalman filter is applied here for short-term forecasting for both one hour and one minute data sets timestep. The presented approach presents interesting results as it allows to improve quasi-systematically the order_1 prediction and Kalman model performances are, for one hour's horizons, competitive with much more complicated models such as ANN which require both consistent historical data sets (at least 200 days) and computational resources (time consuming, Matlab toolboxes, etc.). This method is easily applicable for poor instrumented or isolated sites but it will be tested on several distinct geographical spots.

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