**A SYSTEM OF DIRECT RADIATION FORECASTING BASED ON NUMERICAL WEATHER PREDICTIONS, SATELLITE IMAGE AND MACHINE LEARNING.**

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## 1. Abstract

For the prediction of the power supplied by a concentrating solar power (CSP) plant, in addition to the plant information, direct normal irradiation (DNI) predictions are needed.

The only way of forecasting meteorological information for the next one or two days ahead is the use of numerical weather prediction models (NWPM). Nevertheless, DNI information is not derived from the NWPM, and intermediate calculations have to be made for DNI estimations.

In this paper we present the prediction system developed by CENER. The goal of the system is to generate DNI forecasts being useful to CSP management and greed integration. The CENER's BSRN station has been used to check the model results.

## 2. Introduction

DNI forecast are needed by concentrating solar power plants to achieve an optimal management of the production, optimal greed integration and to allow the electrical market access. These goals force to generate predictions with a horizon of, at least, one day ahead. Nowadays, only the NWPM generate meteorological predictions with this horizon but the DNI variable is not directly predicted by this kind of models. So, it appears the need of different models that allow us to obtain DNI predictions.

Joint to the NWPM there are a set of source information related to the DNI as meteorological ground measurements, satellite images or aerosol data. CENER`s model combine all this information to obtain DNI forecasts with a horizon of a day.

## 3. Related information and system scheme

As we say before, there is a set of different source information related to the DNI in a site. As first way, to generate DNI forecasts we use a NWPM, concretely the Skiron model. It is running at CENER using GFS data as input and with a spatial resolution of 0.1º, hourly frequency and up to six days ahead.

So, to obtain the final DNI predictions our system uses two kind of historical data. First, the satellite images are used to fit a right cloudy model from the Skiron outputs; On the other hand, different ground measurements as DNI, temperature, humidity or pressure are used to implement a DNI model join to Skiron information.

Skiron generates three levels of cloud cover information. We combine these three forecasts to obtain the total cloud cover information with a similar aspect of the satellite images. By mean of a historical of satellite images we fit a model based on kernel functions that obtains the final cloud forecast. Figures 1, 2 and 3 are ax example of the original levels of cloud cover predictions. Figures 4 and 5 show the final cloudy cover forecasts and the corresponding satellite image.

The CENER's prediction model contains two steps to generate the final DNI forecast. In the first one it determines the kind of hour: a clear sky hour or a cloudy one. To do that, we have implemented a classification model based on Support Vector Machines and that uses as inputs the historical of DNI records and the cloudy cover predictions of Skiron. The second phase of the prediction system contains the final determination of the DNI, if the previous classification model predicts a clear sky hour; we apply a clear sky model to generate the DNI data. This clear sky model is based on the close ground measurements. Other case, when cloudy hour was predicted we implement a nonlinear regression model based on Support Vector Machines and some classification techniques to generates the DNI prediction.

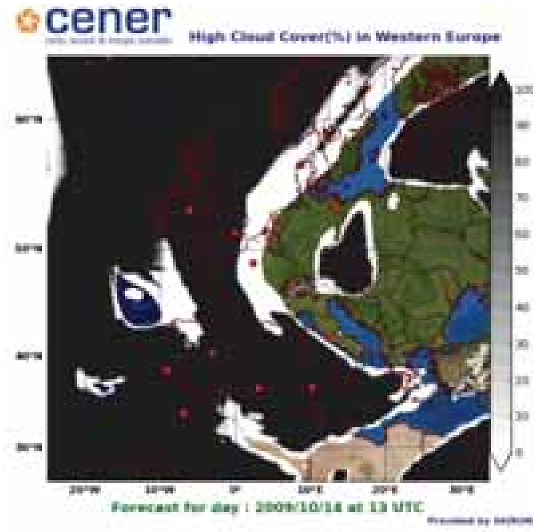


**Fig. 1: High cloud cover forecast**

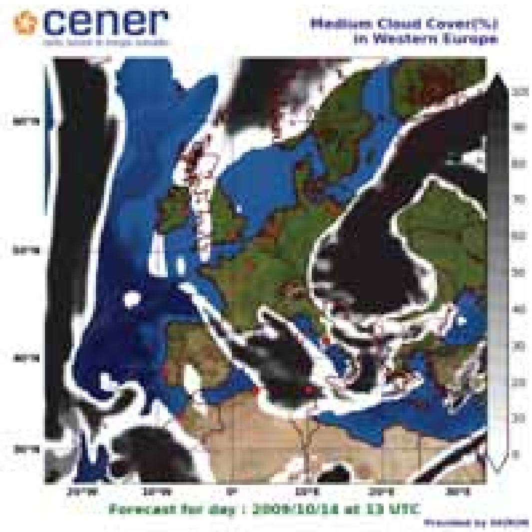


**Fig. 2: Medium cloud cover forecast**

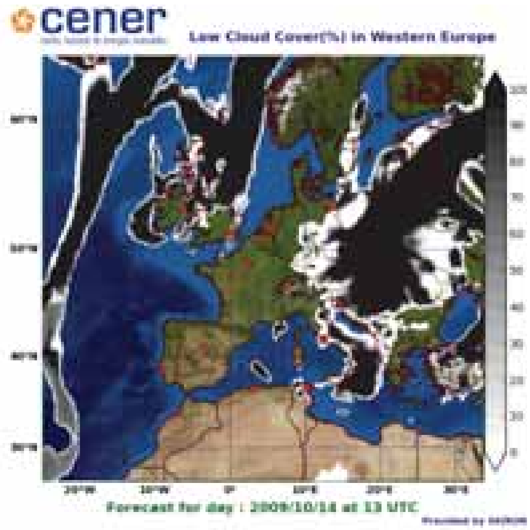


**Fig. 3: Low cloud cover forecast**

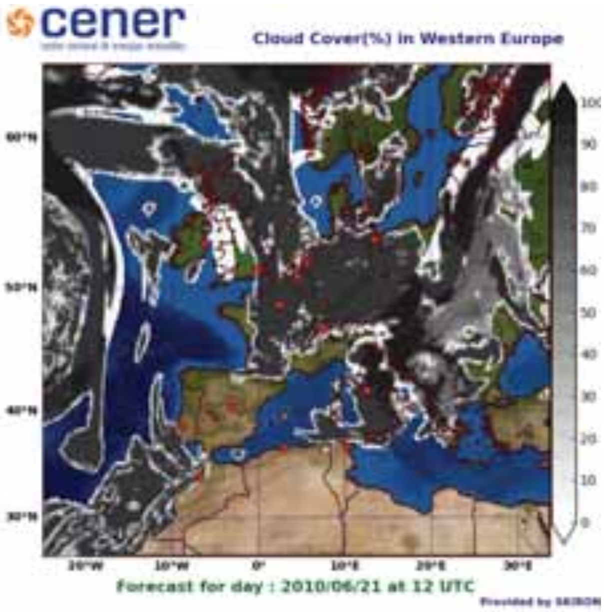


**Fig. 4: Final cloud cover forecast**

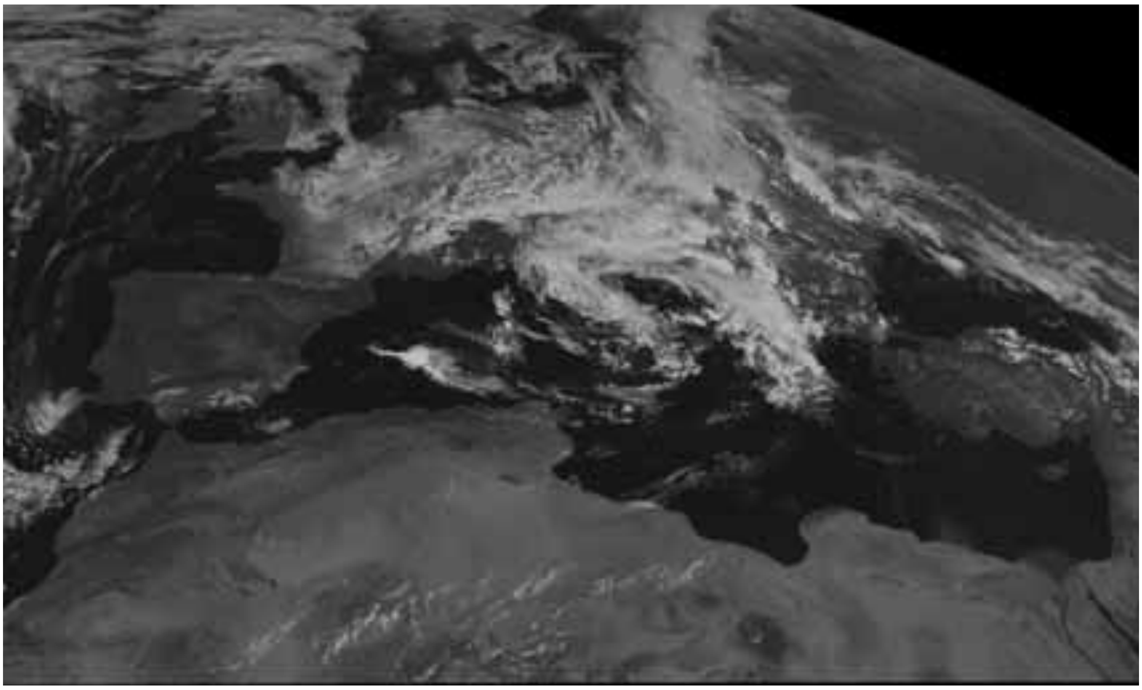

**Fig. 5: Related satellite image**

## 4. Validation of the DNI prediction model

To validate the behavior of the DNI prediction system we use the real data from the CENER BSRN station sited in Sarriguren (North of Spain). A simulation exercise covering since June 2010 to April 2011 was made. The relative MAE was used as error criteria.

Thinking in the operatively of the CSP we also calculate the error level taking into account only those data which make the plant operatively, that is the hourly higher that 400 W/m$^2$. Table 1 contains the error level obtained in the complete period discretizing by DNI levels. We observe how the error decreases with the DNI.

**Tab. 1: Error level by bins of DNI**

| Level | rMAE |
|---|---|
| > 0 | 0.5 |
| >100 | 0.3 |
| >200 | 0.24 |
| >300 | 0.2 |
| >400 | 0.17 |
| >500 | 0.15 |
| >600 | 0.14 |

Monthly studies show how the summer months offers the lowest error levels, less than 15% of error in front of the winter months when the error overcome the 20%. These results are collected in table 2.

**Tab. 2: Monthly Error levels**

| Month | rMAE |
|---|---|
| 201006 | 0.11 |
| 201007 | 0.15 |
| 201008 | 0.14 |
| 201009 | 0.18 |
| 201010 | 0.22 |
| 201011 | 0.29 |
| 201012 | 0.22 |
| 201101 | 0.20 |
| 201102 | 0.19 |
| 201103 | 0.20 |
| 201104 | 0.16 |

To finish it is important to sign that a 85% of the hourly data have been correctly predicted in the sense that they were operatively data or not. That is, it is very important to the plant management that, if the real data will be greater than 400 $W/m^2$ the prediction were also greater than this level and, also if the real data will be lower than this reference level, the DNI forecast must detect this case.

## 5. Conclusions

We present a prediction system whose principal goal is to allow the correct management of the CSP plants. In this sense, the objective of the system depends of the needs of the plants, for example the accuracy is important in cases of relatively high radiation levels (> 400 $W/m^2$ ). In the case of study we predict correctly the DNI level in an 85% of the hours.

Respecting to the error level a lowest error of 11% (rMAE) has been obtained in some summer months, meanwhile in winter months the error level overcomes the 20%.

## 6. References

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