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Clustering weather situations with respect to prediction of solar irradiance by multiple NWP models

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Abstract. With the photovoltaic (PV) and concentrating solar power (CSP) forming a growing portion of European power sources, there is a strong demand for a reliable prediction of solar power. Such predictions are mostly provided by physical or statistical models, both of which rely on accurate forecast of solar irradiance. For the short-to-medium-term forecast horizon (hours to days), irradiance forecast is provided mostly by numerical weather prediction (NWP) models. However, in spite of a recent effort to improve irradiance prediction within current NWP models, its quality is still not satisfactory and it is responsible for a majority of uncertainty in photovoltaic power forecasting. A promising method of improving NWP solar irradiance prediction is multi-model approach. This paper presents preliminary results from a data mining approach to combining irradiance forecasts from multiple NWP models.

1 FORECASTING SOLAR IRRADIANCE

Forecasting photovoltaic and concentrating solar power production is crucial for three main purposes: grid balancing, electricity market trading and planning of maintenance tasks (excluding solar resource assessment, which requires rather climatological data). Various approaches have been used for solar power modeling, ranging from purely physical models, statistical approaches, black-box models like artificial neural networks and hybrid models combining some or all of these [4]. Depending on usage, a solar power model may provide either a point forecast or some form of uncertainty measure. As the power output of solar plants depends mainly on solar irradiance, any solar power model that goes beyond the forecast horizon in which pure persistence or time-series approach is usable (three hours at most) needs solar irradiance forecast as an input.

Nowadays, the most ubiquitous method of providing forecasts of irradiance, as well as other meteorological variables, are numerical weather prediction models[2]. These are usually highly complex and computationally demanding models that represent atmosphere as a three-dimensional grid and combine numerical solution of physical processes with simplifying parametrizations to model such a chaotic system as weather is. An NWP model may be either global or local, which models a limited area in detail and requires lateral boundary conditions from a greater area model. A mesoscale NWP model provides forecasts of meteorological variables with horizontal resolution around 1–30 km and a forecast horizon up to few days with usually hourly time steps.

Quality of NWP irradiance forecasts differs greatly not only between different models, but also depending on type of weather involved. Stable weather in general is more predictable by NWP, specifically clear-sky solar irradiance forecasts are very accurate, while fronts, convection or fog may lead to high forecast errors. It has been demonstrated that averaging forecasts from different NWP models leads to reduction in RMSE and fewer extremely poor forecasts [2] and that correcting model bias for separate weather types is beneficial [5]. This experiment intends to take advantage of both of these properties by using different averaging weights based on weather patterns identified by supervised learning. Clustering has already been used to further specify NWP outputs [9].

2 DESIGN OF THE EXPERIMENT

For a pilot experiment, forecasts of hourly averages of global horizontal irradiation (GHI) produced by four different NWP configurations (see Table 1) have been combined to fit measurements from 15 professional weather stations operated by Czech Hydrometeorological Institute. Irradiance forecasts from the MM5 model [3] and its descendant WRF [8] have been previously demonstrated to differ not only when using different parametrization modules [1], but also significantly between model versions [2], see Figure 1.

Table 1. Configuration of NWP models used in the experiment

Model	Version	Radiation scheme	Cumulus parametrization	Vertical levels
MM5	3.6	RRTM	Grell	26
MM5	3.7	RRTM	Grell	31
WRF	2.2	Dudhia	Kain–Fritsch	39
WRF	3.4	Goddard	Grell	39

All of the models shared identical nested domains (9×9 km horizontal resolution covering Czech Republic and 27×27 km covering central Europe) and used NCEP GFS[3] model outputs as initial and boundary conditions. They were run in a simulated operational regime, producing a new 48-hours long forecast every 6 hours, between May 2011 and April 2012. Dataset has been split by date into 20 segments, each having 15 days of training data and 3 days for validation.[4]

Four control experiments have been made:

1. Each model corrected by removing bias separately for cases with similar solar zenith angle and clearness index as suggested by [5]

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[2] Other popular methods include nowcasting of cloud patterns using satellite and/or other data, these are useful for shorter horizons of up to few hours.

[3] Global Forecast System, National Centers for Environmental Prediction, USA

[4] Detailed experiment specifications can be requested from author.

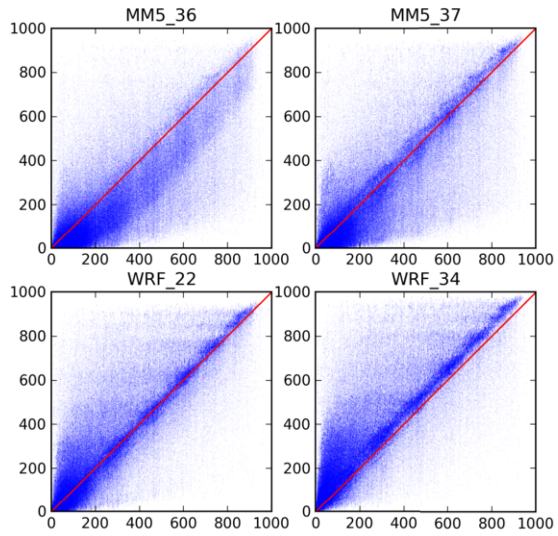

Figure 1. Scatterplots of uncorrected models versus observation

2. Linear combination of uncorrected models
3. Linear combination of models corrected as in 1
4. Linear combination of models with separate coefficients for data similarly stratified as in 1

The results (Table 2) indicate a strong improvement by bias correction and by linear combination themselves, but negligible improvements/overfits by using both and by stratified combination.

3 PROPOSED METHOD

The main idea in the proposed method is to cluster meteorological data not by an unsupervised learning, but rather to identify such clusters of weather sitiuations that have different expected errors for each model. Therefore, decision trees have been selected as regression technique with the ability to separate clusters of input data.

The trees are built by the CART regression tree algorithm [6] implemented in the scikit-learn library [7]. Basic meteorological variables, measurement metadata (latitude, longitude and altitude) and season are used as input variables, the target variable is deviation of each of the models.

The learning algorithm is expected to recognize such weather patterns for which each of the models has homogeneous error behavior (low error variability and easily removable bias). It is further expected that due to tree size limits (maximum depth and minimum samples per leaf), some of the clusters will not reach this objective, yet they can still have different variance of deviation of each model than the whole dataset. To make use of this potential information, a linear regression is used to find optimal linear combination of models in each cluster of the training data, therefore the decision tree itself is used only for clustering and not as a direct predictor.

To improve generalization, random forest is used instead of a single decision tree, providing multiple partitions of the dataset. The optimal linear combination of models has to be found for each cluster of each partitioning, and the final prediction of the forest is defined as average of predictions by each tree.

Table 2. Experiment results

	RMSE [W·m^{-2}]	
Model	in-sample	out-sample
MM5 3.6		158.0
MM5 3.6 ⊙	140.4	144.0
MM5 3.7		146.5
MM5 3.7 ⊙	141.4	149.3
WRF 2.2		140.7
WRF 2.2 ⊙	123.1	121.6
WRF 3.4		167.9
WRF 3.4 ⊙	131.4	133.7
Simple combination	115.1	115.4
Combination of ⊙	114.3	115.7
Stratified combination	113.6	115.8
Random forests	106.3	113.2

⊙ = bias correction on stratified data

Result of the preliminary experiment (Table 2) shows a modest improvement which, however, was not achievable by the control methods. Top levels nodes of the decision trees contain rules that are consistent with current experience with NWP irradiance prediction.

4 FURTHER RESEARCH

There is still a lot of room for improvement of results with the proposed random forest method. Most importantly, only point predictions of meteorological input variables at the measurement location were used. The predictability of weather by NWP models is however a very complex phenomenon. For further research, more spatial and temporal information is going to be provided (averages and variabilities for different size areas, trends).

In order to evaluate generalization capabilities of this method, the pilot experiment was purposely restricted from learning individual parameters for each station, thereby completely excluding local post-processing, which is very useful for NWP outputs in most cases. A more complex local information is going to be used by clustering meteorological variables within the 3D grid.

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