Multi-Model Ensemble for day ahead PV power forecasting improvement

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Summary

The aim of the paper is to compare several data-driven PV power forecast models using different Numerical Weather Prediction (NWP) input data and then to build up an outperforming Multi-Model Ensemble (MME) and its prediction intervals. Statistic, stochastic and hybrid machine-learning algorithms were developed and the NWP data from IFS and WRF models were used as input. The MME built up using data-driven forecast produced by the different models improves the performance of the best model of the ensemble, bringing the skill score from 42% to 46%.

Purpose and approach

The purpose of this work is to improve medium term forecasting (day ahead) of PV power production using a multi-model ensemble technique. The accuracy in forecasting PV power is of great relevance when high PV generation requests greater secondary reserves and ready supply to overcome the unpredictability and variability of the residual load. Moreover this large amount of energy needed to ensure electrical balancing has to be purchased at a higher price on the Real-Time Energy Market. Thus improvement of accuracy, reducing unpredictability, reduces also energy costs.

In the last five years a data-driven approach has been extensively tested for PV power generation forecast for the 24/72 hours horizon. This approach involves a wide range of machine learning methods that can be built using historical data. These statistical or stochastic models try to reconstruct the relationships between input and output data sets. They do not require knowledge of the physical laws describing the phenomenon and none or very little plant information. Once trained, these algorithms can use a variety of NWP products to directly provide the PV generation forecast. Hybrid models could be obtained using different models in series. If different predictions are combined together a Multi-Model Ensemble can be obtained (see fig 1).

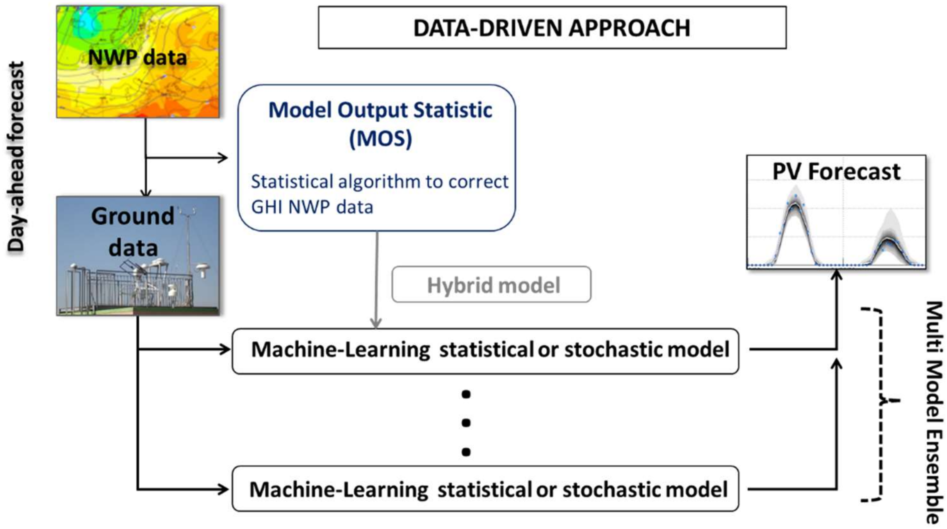

Figure 1: Schematics of data-driven approaches for day ahead PV power forecast.

The approach presented consists in the development and test of various data driven forecasting models applied to different Numerical Weather Prediction (NWP) data sources and in the investigation on how to build an outperforming multi model ensemble.

Two different NWP data coming from the global model IFS of the ECMWF and from the mesoscale model WRF, were used. Moreover, the WRF-RRTM irradiance forecast was refined with a Model Output Statistic post-processing algorithm (MOSRH), to improve prediction accuracy. A Support Vector Machine algorithm was developed, named GTSVM(ECMWF). Two stochastic models based on an ensemble of Artificial Neural Network were also built: RHNN(WRF) and GTNN(ECMWF). Then a hybrid model based on the model chains of MOSRH and GTNN, namely, GTNN(MOSRH(WRF)), was used to study the impact of the different Irradiance predictions on the accuracy of the power forecast. Finally an outperforming Multi-Model Ensemble (MME) was generated together with its prediction intervals. Four years of monitored weather and production data from a 662 kWp Cadmium Telluride PV plant, located in Bolzano (Italy), were employed to train and test the models.

Scientific innovation and relevance

A variety of data driven models using different techniques were developed by various authors. Although literature and methodology are established for single models, a Multi Model Ensemble approach has not been fully explored yet. Our results could contribute to improve the knowledge of solar and PV forecasting, deepening the concept of multi-model ensembles. In particular, some relevant questions related to data driven approaches have been investigated: using different irradiance predictions (NWP) as input for the same model, does the outperforming NWP produce also the best power forecast? How much could the accuracy change, if, on the contrary, the same NWP input is used for different kind of models? How can an outperforming Multi-Model Ensemble be constructed and what is the improvement with respect to the best forecast model of the ensemble? How can prediction intervals be estimated?

Moreover, in the paper a new parameter called Clear Sky Performance index, was defined. It was used both to develop the stochastic model and to set up an outperforming persistence model. This parameter could be considered as the equivalent of the clear sky index for PV power generation.

Results and conclusions

Figure 2 (A) shows the yearly average accuracy of all the models together with the Persistence Model (PM) skill score (in bracket). In the irradiance forecast community the persistence model used as reference is usually the one obtained by the clear sky index since it achieves a lower RMSE with respect to the trivial persistence. Similarly, for the power forecast, the persistence calculated using the new Clear Sky Performance index (KPM) shows a 10% skill score with respect to the trivial PM, so that it could be used as a better benchmark model.

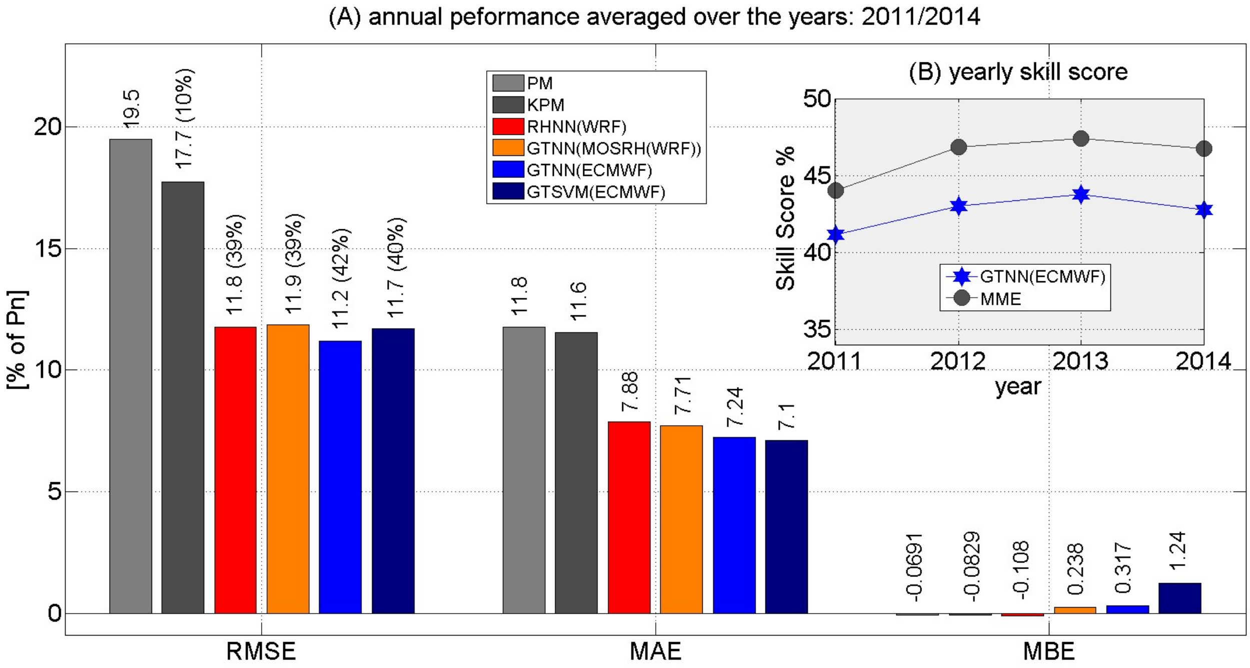

Figure 2: accuracy comparison of PV power generation forecast (yearly average), in brackets the skill score of the model (A); yearly skill score of the MME and of the best forecast of the ensemble (B).

The RHNN(WRF) model that uses the WRF prediction of relative humidity to provide the PV power forecast achieved the same accuracy of the hybrid model GTNN(MOSRH(WRF)) that used the GHI prediction of WRF-RRTM post-processed by the MOSRH algorithm, reaching a skill score of 39%. This means that MOSRH and RHNN provide a similar correction to the WRF output.

The same stochastic model GTNN was used with different Global Horizontal Irradiance (GHI) prediction sets as input (ECMWF and MOSRH(WRF)). ECMWF exhibited a Mean Absolute Error (MAE) of 76 W/m^2 on the GHI prediction while MOSRH(WRF) achieved a MAE of 70%. Nevertheless the low performing NWP input (ECMWF) produced better power performance. Indeed the skill score of GTNN(ECMWF) was 42% while the skill score of

GTNN(MOSRH(WRF)) was 39%. This apparent inconsistency depends on the capability of the machine learning model to correct the errors of the input data.

The models GTNN(ECMWF) and GTSVM(ECMWF) that use the same input data show similar performance: a skill score of 11.2% and 11.7% respectively. Thus, the stochastic and statistical non linear approaches are substantially equivalent.

The Multi-Model Ensemble (MME) was obtained averaging the four forecasts. Figure 2 (B) shows yearly skill score of the MME and of the best forecast of the ensemble. The MME achieved a considerable performance improvement. It reached a RMSE of 10.5% of Pn and a skill score of 46%. The MME outperformed the best model of the ensemble, since forecast averaging reduced the noise of each single predictor. In particular, to reach this improvement the ensemble should include all forecast trajectories with similar accuracy (around 1% of difference in RMSE) but generated by different algorithms and using different NWP forcing.

The prediction intervals could be effectively used to predict the amount of secondary reserve with a fixed confidence level. They were calculated for the MME prediction with the same ANN technique used to provide the forecast.

It was proved that the probability of the observation falling inside the prediction interval is always greater than the corresponding confidence level. Thus a reliable estimation of these intervals was provided. Moreover, as for irradiance forecast, it was proved that the maximum MME errors appears at low incidence angles in overcast and variable sky conditions (predicted PKcs in between 0.4 and 0.7).

Figure 3 shows the trend of the MME forecast and its prediction intervals for five different typology of days in 2011.

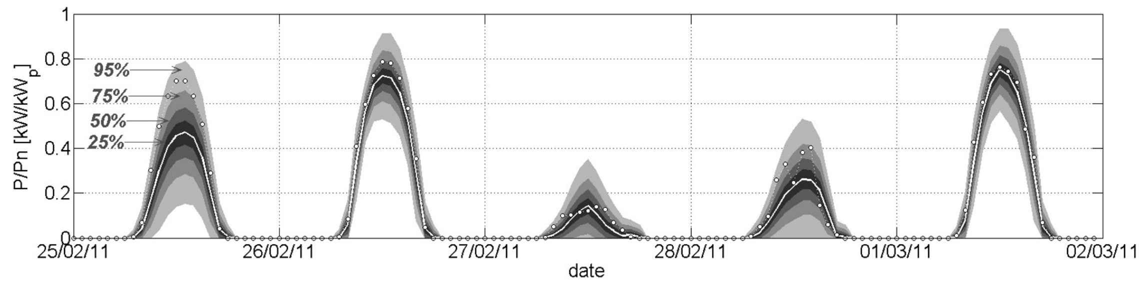

Figure 3: Observation (dots), MME forecast (white line) and prediction intervals (grey lines) for five days of 2011.