# Spatio-temporal models for photovoltaic power short-term forecasting

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*Abstract*—**The interest for photovoltaic (PV) generation has grown in recent years, while some areas start to witness significant penetration of PV production in the grid. However, the power output of PV plants is characterized by an important variability since it depends on meteorological conditions. Accurate forecasts of the power output of PV plants is recognized today as a necessary tool to facilitate large scale PV penetration. In this paper, we propose a statistical method for very short-term forecasting (0-6 hours) of PV plants power output. The proposed method uses distributed power plants as sensors and exploits their spatio-temporal dependencies to improve the forecasts. It uses as input only production data of the geographically distributed power plants, while its computational requirements are small making it appropriate for large-scale application.**

## I. Introduction

Photovoltaic (PV) generation is continuously increasing in Europe. The inherent variability of the PV plants power output due to the weather dependency introduces uncertainties to the network operation and is seen as a challenge by system operators, especially when it comes to large scale integration. The expected production should be accurately forecasted in order to ensure the permanent balance between electric production and consumption. Forecasts of PV generation are also important in minimizing reserve costs [1], for participating of independent power producers to the electricity market, for increasing the competitiveness of the renewable energy technologies [2], for monitoring the production and adjusting the load. They are particularly useful for the management of combined PV and storage power plants that are especially developing in the context of French islands. In the context of smart grids PV forecasts are necessary to manage distribution networks or microgrids where other options coexist to PV generation like active demand, storage etc. [1].

There are several methods in the literature to forecast the PV production. These methods are classified according to their specific forecast horizon [3]. The final choice of a forecasting technique is related to that horizon and the available data. The most usual statistical methods are regressions methods like linear regression, regression trees, boosting, bagging, random forests, Support Vector Machines [4]–[7], and semi-parametric models. These techniques investigate the correlation between the historical production and the related meteorological measurements [8]. The Box and Jenkins time series treatment methods (ARIMA, ARMA, SARIMA, ...) are also widely used in PV forecasting. The delicate question of stationarity of the series are treated by preprocessing steps using either clear-sky modelling, [9]–[11] or some normalisation techniques by Top of Atmosphere (TOA) or Global Horizontal Irradiance (GHI).

Neural networks are also frequently used to forecast the PV production with different types of activation functions [12]. They are often compared or coupled with physical models [13], [14]. They can also be used as a second step in a two-step modelling chain, where the first step is to predict meteorological variables using Numerical Weather Predictions (NWP) [15], [16].

The methods based on exploitation of similarities in historical data is another family of techniques that can be used to forecast PV production. The key principle of these methods is to search and classify in historical data of production and/or meteorological variables the similarities with current conditions. When similar conditions of historical data reoccur, the methods assume that what should happen in the future should be similar to what happened in the past. Data mining techniques are used to cluster the past events [17], [18]. This same idea of similarity is used to forecast the production when the PV panels are covered by snow [19].

There is an increasing interest for techniques which can take into account not only historical data about the site for which the forecasts are made but also other spatially distributed data. These methods are developed for different applications like the identification of a region where the energy production will be optimized [20], [21], the study of the spatial propagation of the forecasting errors [22], [23] or even a "geographically intelligent" prediction [24]–[26]. Most references though refer to spatio-temporal wind power forecasting. For PV forecasting there has been an increasing interest in using spatial information coming from sky images from cameras or from satellite images. The aim is to model in 2D or even in 3D the movement of the clouds and then predict their evolution and consequently the PV plant power output for the very short term (few minutes up to hour) [27]–[29]. These methods are applicable for the very short term and is costly due to the complexity of the needed infrastructure and the modelling chain that has to be developed. Not enough evaluation results are found in the literature with comparison to simpler or reference methods.

In this paper we propose a forecasting methodology within the framework of the use of both spatial and temporal data when developing forecasting techniques. The aim is to propose efficient models for short-term forecasting of PV production, i.e. for a horizon of a few minutes up to 6 hours. The models investigated will use the dispersed power plants as a network of sensors in order to ameliorate the prediction for each of these plants. There is no input from the NWP

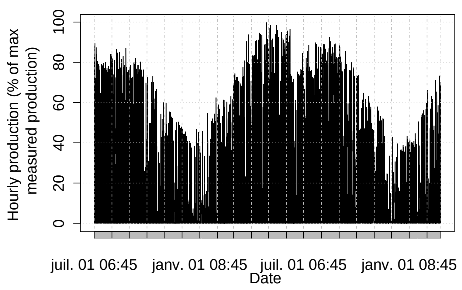


Fig. 1. Normalized hourly production of a power plant over a year period. Normalization is done with the maximum measured production of the plant

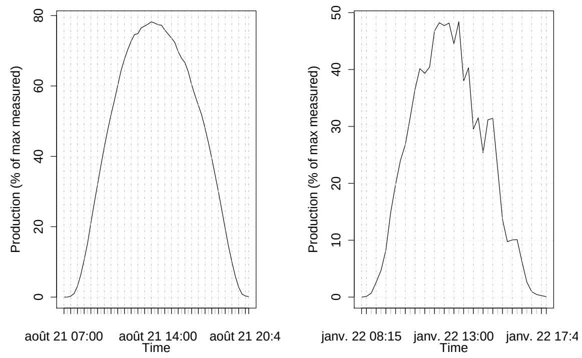


Fig. 2. Normalized production of a power plant over a day period. The right figure depicts a day with high variability of the power output. Normalization is done with the maximum measured production of the plant.

model used when testing the proposed models as we are seeking for models with high updating frequency. The paper is structured as following: the PV production data used in the modelling and the evaluation criteria for the accuracy of the forecasts are presented in section II. It is important for us to present the data at this early point as we used them to operate the choice of the reference model as presented in section III. That choice of the reference model has then been made on the basis of the performance of candidate models evaluated on the test case. The proposed spatio-temporal forecasting technique is also described in section III and the results are presented and discussed in IV. Finally, the conclusions of the study are discussed in section V.

## II. The test case

The data used in this study consist of time series of the measured PV generation of a set of power plants located in the South of France. The data collected includes 9 power plants with peak power ranging from 45 kW to 5 MW. The data cover a period of 20 months starting from July 2013 with a resolution of 6 min to 15 min depending on the measurement site. The data quality has been tested and the inconsistencies have been removed (i.e.cleaning erroneous data, dealing with missing values. Finally the data have been interpolated to generate time series with a common 15 min temporal resolution. Figure 1 represents the hourly production for one power plant of the set for one year. Figure 2 shows a zoom for 2 days of the 15 min production data illustrating the variability in the data.

### *A. Data normalization*

To respect the confidentiality required by the data providers, the data were normalized using the maximum observed production for each power plant. For a plant $x$: $P_t^x \longleftarrow \frac{P_t^x}{\underset{t}{max} P_t^x}$. The resulting data are ranged between 0 and 1 allowing a more suitable format for the prediction models as well as easy interpretation of forecasting errors. When developing the models 15 months are used for learning and 5 for the tests.

### *B. Analysis of spatial correlations*

A study of the relation between the production data of geographically dispersed power plants has been made. The cross-correlation of the observed production has been evaluated for the test case's power plants and presented in table I (for readability only 5 power plants are reported). The distance between the measured data of each pair of power plants is shown in table II. The values observed for these correlations (close to one) suggest a strong correlation between the energy productions of the geographically dispersed sites. That link appears to be stronger when there is a lag on one of the series of production.

| corr | p1 | p2 | p3 | p4 | p5 |
|---|---|---|---|---|---|
| p1 | 1 | | | | |
| p2 | 0.84 | 1 | | | |
| p3 | 0.95 | 0.82 | 1 | | |
| p4 | 0.91 | 0.81 | 0.92 | 1 | |
| p5 | 0.91 | 0.81 | 0.91 | 0.98 | 1 |

TABLE I
Correlations between plants

| d | p1 | p2 | p3 | p4 | p5 |
|---|---|---|---|---|---|
| p1 | 0 | | | | |
| p2 | 354 | 0 | | | |
| p3 | 13 | 352 | 0 | | |
| p4 | 233 | 562 | 244 | 0 | |
| p5 | 235 | 565 | 245 | 2.6 | 0 |

TABLE II
Distance (in km) between sites

To show that, we first evaluate the appropriate lag $h_{max}$ that maximises the correlation between two measures of the $N$ power plants:

$$h_{max} = \underset{h}{\operatorname{argmax}} \;\; corr(P_t^i, P_{t+h}^j), \quad h \in \mathbf{Z}, \quad j = 1, \ldots, N.$$

and the corresponding correlation value. To avoid interpreting the variation of the correlations with the movement of the sun (i.e the lags are just the difference in the position of the sun for the respective power plans), we use the solar time reference that includes the power plants longitude, the equation of time and the solar position [30]–[32]. The solar noon is then the same for all the plants and there is no more East to West correlation transfer according to the position of the farms. The results are respectively presented in the table III and IV and the correlation values indicates an increasing correlation in comparison with the no-lags case. This evolution reflects the link between the past and future production for the geographically dispersed plants and confirm the relevance of a modelling solution that takes into account not only the temporal variability of the production series but also the spatial variability. Though, despite the above performed correction it is obvious that a factor that dominates when forming the correlation values is the bell shape of the daily PV production curves that are similar and highly correlated for all sites. Further study may attempt to eliminate this effect through time differencing for example since what is of interest is the deviations of the bell shape and how these propagate in space. This aspect is further developed in the next Section in the development of the reference model.

| h | p1 | p2 | p3 | p4 | p5 |
|---|---|---|---|---|---|
| p1 | 0 | | | | |
| p2 | 45 | 0 | | | |
| p3 | 0 | 60 | 0 | | |
| p4 | 15 | 60 | 15 | 0 | |
| p5 | 15 | 75 | 15 | 15 | 0 |

TABLE III
LAGS VALUES IN MIN

| corr | p1 | p2 | p3 | p4 | p5 |
|---|---|---|---|---|---|
| p1 | 1 | | | | |
| p2 | 0.94 | 1 | | | |
| p3 | 0.95 | 0.86 | 1 | | |
| p4 | 0.98 | 0.84 | 0.92 | 1 | |
| p5 | 0.97 | 0.84 | 0.91 | 0.98 | 1 |

TABLE IV
CORRELATION BETWEEN LAGGED PRODUCTION SERIES

## III. FORECASTING MODELS

In this section we present the advanced spatio-temporal model developed, as well as a reference model that is proposed to evaluate the benefits from the advanced one.

### A. The choice of the reference model

As presented in the introduction, there are several forecasting methods that can be used to forecast PV generation. In order to identify the appropriate modelling technique, we first rejected the idea of using the persistence model. Despite the popularity of this model in the literature as a reference model, the overall performance is poor. It is noted that persistence may be a good reference model when the aim is to evaluate the performance of a ”classical” advanced model, that is a model that uses only input from the site of the power plant. The aim here is however to show the advantages of using spatially distributed information as input to the forecasting process. For this purpose the ”reference” should be a state of the art model that does not use such information. In order to choose the ”good enough” reference model , we investigated both random forests (RF) and autoregressive (AR) models.

*The Top of Atmosphere radiation as a normalization tool:* The stationarity of the photovoltaic production data is a common problem when developing a forecasting tool because most time series treatment methods (Box and Jenkins) are conditioned by that stationarity. We propose a two-step approach to address this problem. The first step is to simulate the Top Of Atmosphere (TOA) irradiance for all the power plants using their spatial coordinates and inclinations, the time period, and the solar position. The second step is to normalize the production series by either dividing it by the simulated TOA or remove the deterministic part by subtraction of the simulated TOA. We then define two series $S_t^1 = P_t - TOA_t$ and $S_t^2 = P_t/TOA_t$. These two series will be used building and selecting the reference model between RF and AR models.

Let's notice that the series $S_t^1$ and $S_t^2$ although they permit to cancel the deterministic component, they do not fulfil the requirement stationarity. In fact, a study of the autocorrelation of the respective series does not show rapid decrease symbol of the stationarity and the unit roots Dickey-Fuller test also rejected the stationarity of both series. Nevertheless, the obtained series should be at least ”more stationary” in the mean than the original series due to the cancelling of the bell shape effect but still no stationary in the variance. An AR model has then been developed on the original normalized series (by the maximum power observed) and the random forests method have been applied to the series $S_t^1$ and $S_t^2$. The performances of the random forests models are slightly better than the AR models. The mean (over all the horizons) RMSE value are respectively of 9.8% and 10% for RF models on series $S_1$ and $S_2$ when it is 10.7% for the AR model. We thus made the choice of the the autoregressive (AR) model as reference model as it is simpler (principle of parsimony) and more intuitive. The reference model is defined:

$$\hat{P}^x_{t+h|t} = \hat{a}^0_h + \sum_{l=0}^{L} \hat{a}^l_h P^x_{t-l} \tag{1}$$

where $P_t^x$ is the production of the power plant $x$ at time $t$ and $\hat{P}^x_{t+h|t}$ the prediction at horizon $h$. The appropriate maximum lag $L$ is chosen by the minimization of the Akaike Information Criterion (AIC). In the following of the paper the results of this reference model will be compared to those of the new spatio-temporal models proposed. proposed.

### B. The proposed spatio-temporal model

Let $\mathcal{X}$ be the set of $N$ PV plants and $Ls$ the appropriate maximum lag. The regression model is defined with the purpose of taking into account the available information about the PV generation of all the power plants. The variables of the model illustrate the evolution and fluctuation of the production of all power plants. The model is then defined as:

$$P_t^x = a^0 + \sum_{l=0}^{Ls} \sum_{y \in \mathcal{X}} a^{l,y} P^y_{t-l} \quad .$$

The coefficients are estimated by least squares. For an selected horizon $h$, the coefficients $a = (a^0, a_r)$ with $a_r = (a^{l,y})_{0 \le l \le Ls,\, y \in \mathcal{X}}$ are estimated by minimising the Residual Sum of Squares (RSS):

$$RSS(a) = \|\mathbf{P^x} - \mathbf{X}\, a\|^2,$$

with $\mathbf{P^x}$ the measure for the power plant $x$, $\mathbf{X}$ is a $N \times Ls + 1$ matrix the lines of which are the current and lagged production for a power plant $y_i$

$$\mathbf{X} = \begin{pmatrix} 1 & P_t^{y_1} & \dots & P_{t-Ls}^{y_1} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & P_t^{y_N} & \dots & P_{t-Ls}^{y_N} \end{pmatrix}.$$

Suppose $\mathbf{X}$ not singularly, $\mathbf{X}^T\mathbf{X}$ is positive definite and the differentiation of the RSS gives:

$$\hat{a} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{P}^{\mathbf{x}}. \quad (2)$$

The forecast at time $t$ for the horizon $h$ for a power plant $x$ is then defined by:

$$\hat{P}^x_{t+h|t} = \hat{a}^0_h + \sum_{l=0}^{Ls} \sum_{y \in \mathcal{X}} \hat{a}^{l,y}_h P^y_{t-l}. \quad (3)$$

### C. The evaluation metrics

Due to the importance of PV generation forecasts for end-user, as mentioned in the introduction, it is necessary to be able to accompany the forecasts with appropriate sets of metrics for assessing their accuracy. In this section we present the metrics that we use which remain the conventional ones in order to be able to be easily assessed by end-users and also to perform easily comparisons with the results reported in the state of the art. Let $e_{t+h|t} = P_{t+h|t} - \hat{P}_{t+h|t}$ define the forecasting error for the horizon $h$. The statistical metrics proposed for the evaluation of the forecasts are :

- the Root Mean Square Error (RMSE)

$$RMSE_h = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e^2_{t+h|t}}$$

  this metric which is often used in its normalized version (NRMSE) permits to evaluate the forecasts with a square order penalization of large errors.
- the bias evaluator

$$BIAS_h = \frac{1}{n}\sum_{t=1}^{n} e_{t+h|t}$$

- the Mean Absolute Error (MAE)

$$MAE_h = \frac{1}{n}|e_{t+h|t}|$$

Beyond that the evaluation includes analysis of the autocorrelations of the forecasting errors and stationarity tests in order to examine the capacity of the forecast models to extract all the available information in the data and make accurate predictions.

## IV. Results

The spatio-temporal model is applied to the case study data for a 6 hour horizon, and the predictions are compared to those of the reference model. The forecasting errors are evaluated and the normalized RMSE relative to the peak power observed at each plant is computed for each PV installation. Graph 3 represents the improvement of the spatio-temporal model for this metric. Each line represents a power plant. The improvement over the reference model can reach up to 5% for a 2-hours prediction period. This improvement increases to 10% for 4-hours horizon and there is improvement for almost all the power plants. For one of the power plants, we can see that for the first prediction horizon (before an hour and a half), there is no improvement. Furthermore, the improvement is negative meaning that the reference model outperforms the spatio-temporal one for the first prediction horizon for that specific power plant. The trend is reversed for higher horizons confirming the utility of using neighbouring power plants production data as input to the forecast model. Using that information has then shown to bring a significant contribution to the forecast performance improvement.

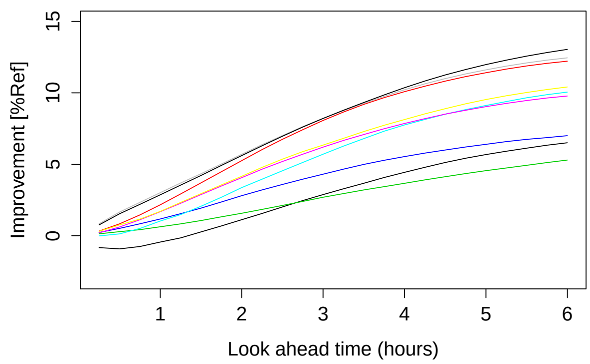


Fig. 3. Improvement of spatio-temporal model over the reference model. Each line represents the improvement obtained for one given power plant.

The criteria MAE and BIAS have been evaluated for each horizon and each power plant. Graph 4 represents for each of the nine power plants of the test case the evaluation of the MAE for both the reference (black line) and the spatio-temporal (red line) model. A significant reduction can be noticed for all the power plants except for the plant 8. This power plant is the same that shows no improvement in terms of RMSE for the first two prediction hours.

Graph 5 represent the evolution of the BIAS criterion for each PV plant and for both models (black is reference and blue is spatio-temporal). Similarly to the analysis is the previous criteria, the spatio-temporal model significantly reduces the bias when predicting the PV production. In almost all the cases the bias is around zero for the spatio-temporal model when it can exceed 5% for the reference model. The most important deviation of the bias in the spatio-temporal case is noticed for the case of plant 8.

The boxplots on the graph 6 present the distribution of the respective MAE and BIAS evaluated on the forecast errors for both the reference and the spatio-temporal models with no distinction of horizon for all the power plants. The significant reduction observed for these two criteria with the spatio-temporal model reinforce the idea that using spatially distributed data in the model is a good way to reduce errors when forecasting PV production. The particularities in the results obtained for plant 8 can be explained by the fact that it's the farthest power plant from all the others in the data set. The spatial correlation between this power plants and the other is very low when not zero.

The presented spatio-temporal method is a simple and efficient way to integrate in the model the spatial variation

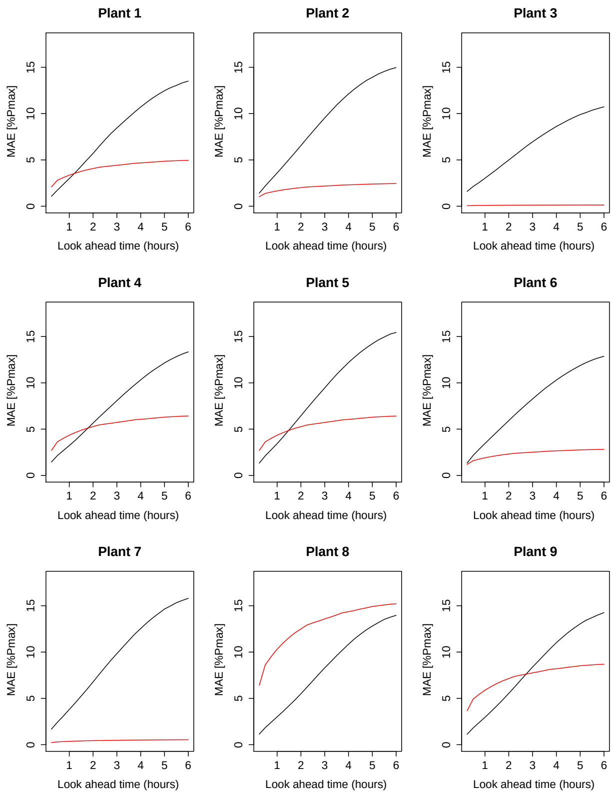


Fig. 4. Evolution of the MAE criterion. One graph per power plant. The black lines and red lines correspond to the performance of the reference model and the spatio-temporal model respectively.

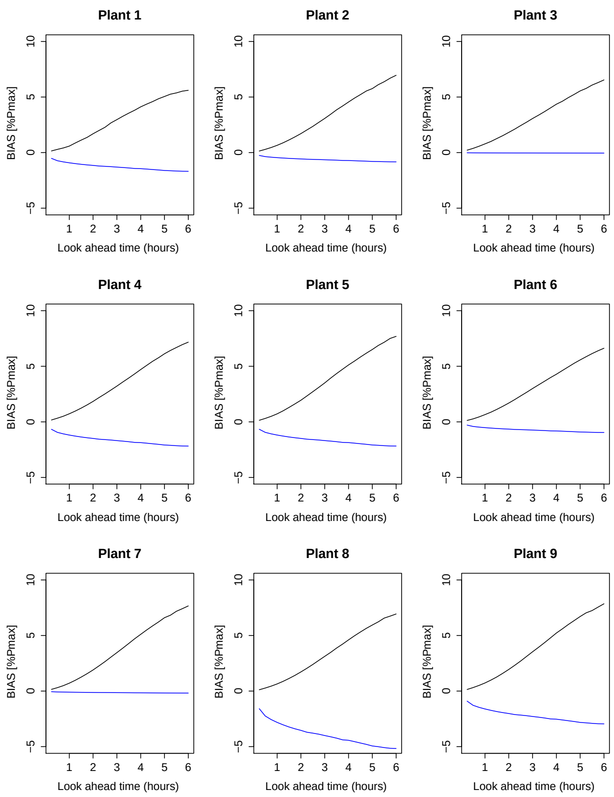


Fig. 5. Evolution of the BIAS criterion. One graph per power plant. The black line is the reference model performance and the blue one the spatio-temporal model one.

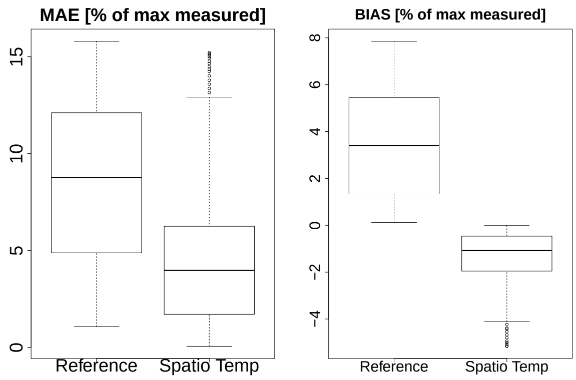


Fig. 6. Comparison of the performance of reference vs Spatio-temporal

of the PV generation. The estimation process is based on least squares regression model easier to interpret and faster to implement than a black box models. This method has been applied to wind power forecasting and showed efficiency in the improvement of the forecast accuracy.

### *A. The parallel with spatio-temporal models for wind power forecasting*

The aim of this paragraph is to present the parallel for the wind power forecasting case. Spatio-temporal models were initially developed for improving wind power forecasts for the short-term (up to 6 hours). It is of interest to see what is the level of results that can be obtained if we apply the same type of model proposed above for the spatiotemporal forecasting of PV generation.

When dealing with wind power plants, an interesting test case is the country of Denmark due to the existing high wind penetration, which is expected to further increase thanks to the ambitious target of the country for renewable penetration by 2025 [33]. The geography in Denmark is smooth and flat, there is only one prevailing weather front dominating in the whole territory at any given moment. The spatio-temporal model proposed above for the case of PV generation has been applied to the Western Denmark area. The data cover 4 years with a 15 min resolution and come from 200 transformation stations, represented as polygons in figure 7. The data has been rescaled for each power plant by a maximum level of production observed normalisation. Two years are used for learning and two for the tests

The spatio-temporal model is applied to the case study data for a 3 hour prediction horizon and the predictions are compared to those of the same reference model as in the PV case. For each of these approaches, the forecasting errors of each wind farm are evaluated and the Root Mean Square Error (RMSE) normalized by the nominal power are evaluated for each power plant. Figure 8 represents the observed improvement for each of the wind farms, one line per farm. The improvement over the reference model can reach up to 20% for 1 hour look ahead time. The results indicate that using spatio-temporal information about the production of the neighbouring farms has a significant contribution on the forecasts performances. Furthermore the proposed model can be used for both types of renewable generation. This is an interesting result when it comes to

Fig. 7. Western Denmark's wind power plants

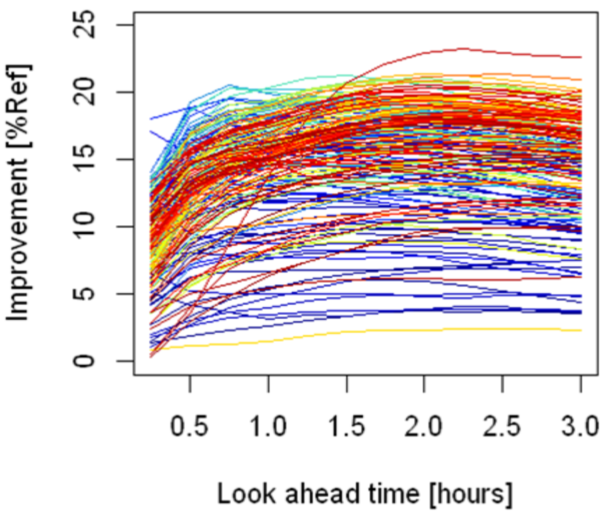


Fig. 8. Improvement of spatio-temporal model over the reference model. Each line represents the improvement for one given power plant (over the 200 considered transformation stations). The color of the lines indicates whether the wind farm is located in the east of Denmark (red lines) or the West of Denmark (blue lines).

implement the forecasting models into operational systems.

## V. Conclusions

In this paper, we have proposed a statistical spatio-temporal model to improve short term forecasting of the photovoltaic generation. The model has been developed and its results analysed on a realistic case study with several power plants geographically dispersed. This model has shown a significant improvement in the forecasting accuracy by reducing the errors. The improvement can be up to 10% in terms of errors reduction (RMSE) and a significant improvement is also observed when investigated criteria like BIAS and MAE. The same spatio-temporal model was also tested for a different application, that of wind power forecasting showed significant improvement for wind power plants production forecasting. These results confirm the benefits of using spatio-temporal data, while modelling short-term generation of PV farms. The spatial information can be taken into account by other techniques in order to improve the current model.

Further work can be to go beyond the linear modelling of the spatio-temporal data by using more complex relations like polynomial estimation or splines. The integration of meteorological data could also be investigated either as a parameter of the coefficient to estimate in the spatio-temporal model or by integrating sky images obtained by cameras or satellites. The integration of the dynamic evolution of meteorological data in the spatio-temporal model is promising for further work.

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