A study on the minimum duration of training data to provide a high accuracy forecast for PV generation between two different climatic zones

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Abstract:

This study focus on the minimum duration of training data required for PV generation forecast. In order to investigate this issue, the study is implemented on 2 PV installations: the first one in Guadeloupe represented for tropical climate, the second in Lille represented for temperate climate; using 3 different forecast models: the Scaled Persistence Model, the Artificial Neural Network and the Multivariate Polynomial Model. The usual statistical forecasting error indicators: NMBE, NMAE and NRMSE are computed in order to compare the accuracy of forecasts.

The results show that with the temperate climate such as Lille, a longer training duration is needed. However, once the model is trained, the performance is better.

Keywords: PV forecasting models, neural network, multivariate model, forecasting errors, training duration.

1. Introduction

With the support of environment policies and the increase of the fossil fuel price, renewable energy sources have been growing strongly in the last few years. The electric power produced by these intermittent sources shows strong variations (sudden and with large amplitude), which must be always compensated on the grid by others dispatchable sources (Ernst et al., 2009), (Do et al., 2010), (Do et al., 2011).

These large variations can put a pressure on the balance of supply/demand of the power system, especially in non-interconnected systems, such as island areas. In the case of French islands for which Island Energy System is the electrical system manager, in order to ensure the stability of the power system, a ministerial decree of 2008 set the penetration rate at 30%, beyond which the system operator is permitted to disconnect intermittent energy (CRE, 2009). Note that this rate of 30% was achieved for a few hours in 2012 in Reunion and in Guadeloupe, resulting in the disconnection of certain facilities of PV production.

The forecast of these fluctuation sources across the concerned islands should allow a better control of the availability of renewable energy production, and thereby reduce the pressure on the balance of supply/demand. Moreover associated with power storage unit (batteries or STEP, for example) will help providing various services to the power system, from ancillary services (adjusting voltage, frequency) to smoothing peak hours. The forecast of fluctuation sources will contribute to the optimization of the design and the use of these storage units.

Generally, the PV production forecast is classified into 2 categories: the day ahead (DA) forecast and the hour ahead (HA) forecast, depend on the domain of application (IEA, 2013).

- The day ahead (DA) forecast is usually based on the numerical weather prediction models. They are dynamical equations that predict the evolution of the atmosphere up to several days ahead from initial conditions. From the forecast of weather condition, the output power

of PV can be estimated (Beyer HG et al., 2009), (Lorenz E et al., 2008), (Traunmüller W & Steinmaurer G., 2010).

- The hour ahead (HA) forecast is usually based on stochastic learning techniques. The underlying assumption of these techniques is that future value of PV production can be predicted by training the algorithms with historical data (Fernandez-Jimenez et al., 2012), (Pedro & Coimbra, 2012), (Mandal et al., 2012).

To generate a prediction of the PV production using stochastic learning techniques, it is necessary to have historical data. These data are used for the learning phase of forecast models of PV production at the studied site (IEA, 2013).

In the literature, several studies have been conducted on the methodology for the forecast of PV generation (Shi et al., 2012), (Krömer et al., 7–11 July 2012), (Lorenz et al., 2012). The authors generally use two historical years: one year for training the model and another year for the test phase. In the literature, the analysis of the minimum duration for the phases of test and training data is little documented.

The proposed study will determine the minimum of historical experimental data necessary to achieve a high accuracy forecast, which can be quantified by a set of several statistical error indicators. There are some works in other areas that focus on this problem (Fine & Turmon, 1994), (Thirumalainambi, 2003), (Cui et al., 2004) but a study on the prediction of PV generation, to our knowledge, is not yet performed.

There are two major factors that affect the time required for the collection of historical data, they are the climatic conditions at the PV site and the statistical model used for the forecast.

The climatic conditions at the PV site affects the level and the type of data fluctuation. The more fluctuate the data is, the more they are difficult to predict, i.e.: the error on the forecast is higher. Therefore, the duration of the data collection is supposed to be longer. In this study, we

investigate the influence of climatic conditions on the historical data necessary for a forecast of PV production by comparing two sites of PV generation with very different climatic conditions: one in Lille, in northern France and the other one in Guadeloupe, in the Caribbean.

The forecasting model also has a large influence on the duration required for the collection of historical data. There are simple forecasting models that requires a few data for the learning phase. The more complex the forecasting models is, the more historical data is needed but the result is often more accurate.

In this study, we will compare some of the most popular statistical models in forecasting PV production: Artificial Neural Network (ANN) (Yona et al., 2007), (Fernandez-Jimenez et al., 2012), (Mandal et al., 2012), Multivariate Polynomial Model (MPM) (Dazhi, 2012), (IEA, 2008) and the Scaled Persistence Model (IEA, 2013).

2. Input data and site description

In this paper, we will use PV production at time (h) and two exogenous inputs: the cloud cover and the air temperature, also at time (h), to forecast the PV production at time (h+1).

For each hour (h) considered as the beginning time of the forecasting, the input vectors are given by:

$$x(h) = \left[N(h); T_a(h); P_m(h)\right] \quad (1)$$

Where: - $N(h)$ is the cloud cover measured at time (h)

- $T_a(h)$ is the ambiance temperature measured at time (h)

- $P_m(h)$ is the average output power produced by the PV system in the previous 60 minutes respective to the h-hour

a. Data measured in Guadeloupe, tropical climate

The PV system installed in Guadeloupe (16°14'36.0"N 61°33'25.9"W) has 832 membrane PV modules of 136Wp each, which makes a total of 113kWc.

The system consists of two inverters. The data logging of PV output power (in W) is integrated in these inverters (collected every 5 min). The two exogenous inputs: cloud cover (in octa) and air temperature (in °C) are measured every hour by the weather station at the airport nearby (Raizet Airport) by Meteo France. As during the night, the forecast is not necessary because the output power of PV is zeros, the study takes into account only the data between 7a.m and 17p.m every day.

The average output power of PV in every hour is calculated from the measurement every 5 minutes of the inverters:

$$P_m(h) = \frac{1}{12} \sum_{t=h-55\text{min}}^{h} P(t) \tag{2}$$

The forecast models will be studied with a varying training period from one month to one year (365 days) and a testing period of 331 days. The output power of the PV system at time (h+1), $P_m(h+1)$ will be predicted from three inputs: $N(h)$, $T_a(h)$ and $P_m(h)$.

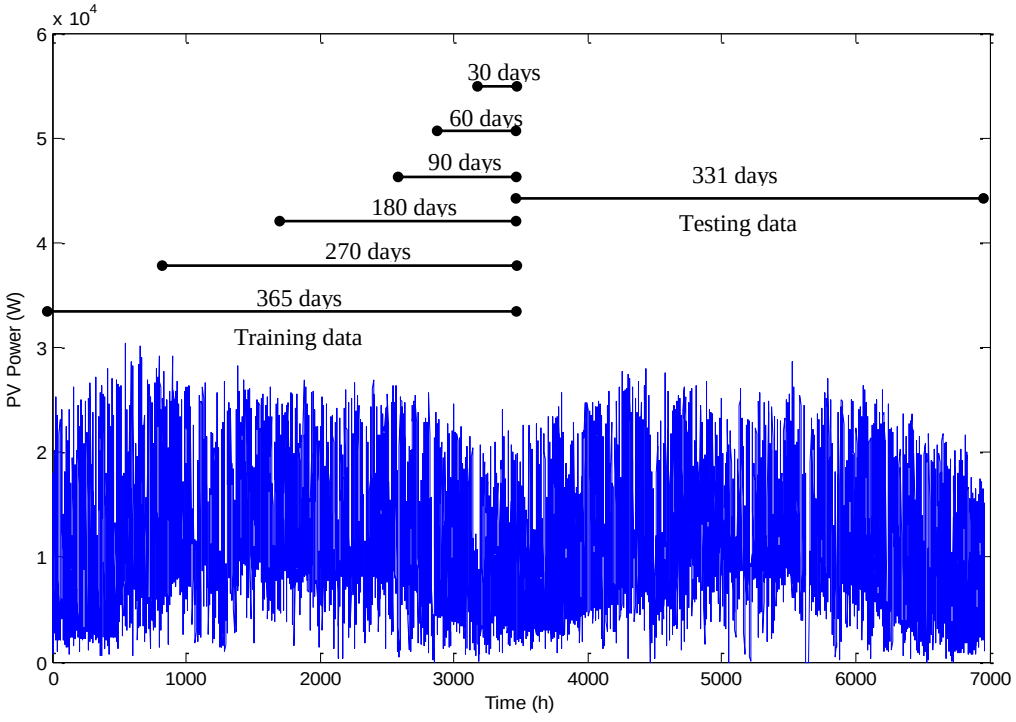

Figure 1. Output power for training and testing in Guadeloupe

b. Data measured in Lille, temperate climate

The installation of a 93kWc PV system in Lille (50°38'58.7"N 3°09'04.3"E) consists of 452 panels. Among these panels, 376 modules have an inclination of 3° and the inclination of the rest is 60°.

The system consists of 31 inverters. The data logging of PV output power (in W) is integrated in these inverters (collected every 10 min). The two exogenous inputs: cloud cover (in octa) and ambiance temperature (in °C) are measured every hour by the weather station at the airport nearby (Lesquin Airport) by Meteo France. As the sun rise is later in Lille, the study takes into account only the data between 10a.m and 17p.m every day to avoid the zero output power of PV during the night.

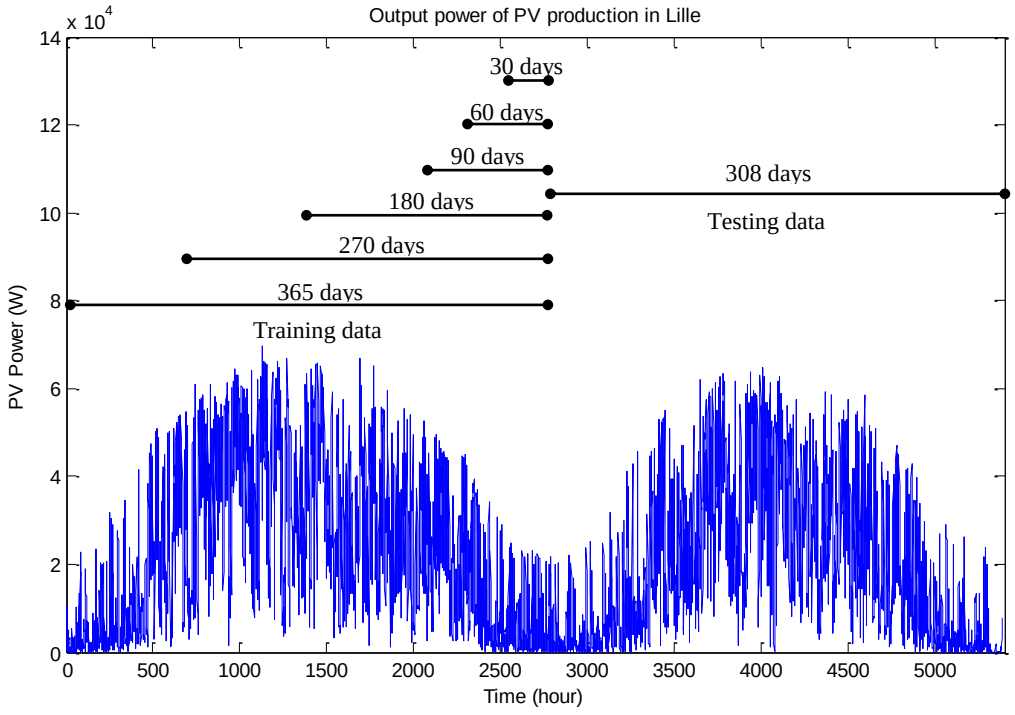

Figure 2. Output power for training and testing in Lille

The average output power of PV in every hour is calculated from the measurement every 10 minutes of the inverters:

$$P_m(h) = \frac{1}{6} \sum_{t=h-50\min}^{h} P(t) \tag{3}$$

The forecast models will be studied with a varying training period from one month to one year (365 days) and a testing period of 308 days. The output power of the PV system at time (h+1), $P_m(h+1)$ will be predicted from three inputs: $N(h)$, $T_a(h)$ and $P_m(h)$.

c. Evaluating the quality of forecast

The precision of the forecast will be evaluated using the following statistical error indicators:

- Normalized mean bias error (%)

$$NMBE = \frac{1}{M} \frac{\sum_{h=1}^{M} P_m(h) - \tilde{P}_m(h)}{\max(P_m) - \min(P_m)} \times 100 \tag{4}$$

- Normalized mean absolute error (%)

$$NMAE = \frac{1}{M} \frac{\sum_{h=1}^{M} \left| P_m(h) - \tilde{P}_m(h) \right|}{\max(P_m) - \min(P_m)} \times 100 \tag{5}$$

- Normalized root -mean-square error (%)

$$NRMSE = \frac{\sqrt{\frac{1}{M} \sum_{h=1}^{M} \left(P_m(h) - \tilde{P}_m(h) \right)^2}}{\max(P_m) - \min(P_m)} \times 100 \tag{6}$$

Where: - $P_m(h)$ is the average output power produced by the PV system at hour (h)

- $\tilde{P}_m(h)$ is the predicted output power of the PV system at hour (h)

- M is the number of hours considered

3. The forecasting models

In this research, the forecasting models will take into account the data of PV production at time (h), $P_m(h)$ and two exogenous inputs: the cloud cover $N(h)$ and the air temperature $T_a(h)$, also

at time (h), to predict the PV production at time (h+1). As the PV production depends on the position of the sun in the day while others input variables does not, a normalization is needed to eliminate this subordination. The input of the PV production at time (h) becomes now $\overline{P}_m(h)$, the normalized value of the PV production with respect to the maximum value at time (h), $P_{max}(h)$.

The absolute value of the PV output power prediction is then obtained by multiplying this normalized value with the maximum value of PV production at time (h+1), $P_{max}(h+1)$. This maximum value can be evaluated from the GHI_{max} curve with the following equation:

$$P_{\max} = \frac{GHI_{\max}}{\max(GHI_{\max})}.PV_{installed} \tag{7}$$

The Global Horizontal Irradiance (GHI) is the total amount of shortwave radiation received from above by a surface horizontal to the ground, which consists of the direct irradiance and the diffuse irradiance. The GHI_{max} is the GHI calculated in the condition of clear sky, using the Kasten clear sky models. (Kasten, 1980)

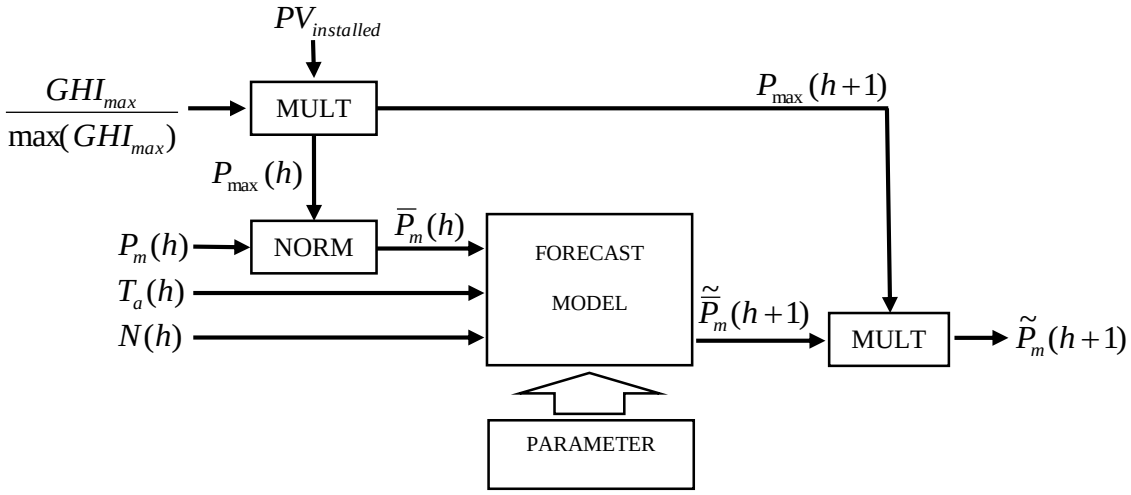

Figure 3. General process of the PV output power forecast

a. Artificial Neural Network

The Artificial Neural Network used in this research is a feedforward neural network for non-linear regression with 1 hidden layer. The choice of the number of neurons in the hidden layer is a complicated issue. In this paper, a value of 4 is chosen based on several researches in literature (Blum, 1992), (Swingler, 1996), (Berry & Linoff, 1997), (Boger, 1997). The Artificial Neural Network will be trained by the historical data with the supervised learning technique, using the Levenberg-Marquardt algorithm (Seber & Wild., 2003).

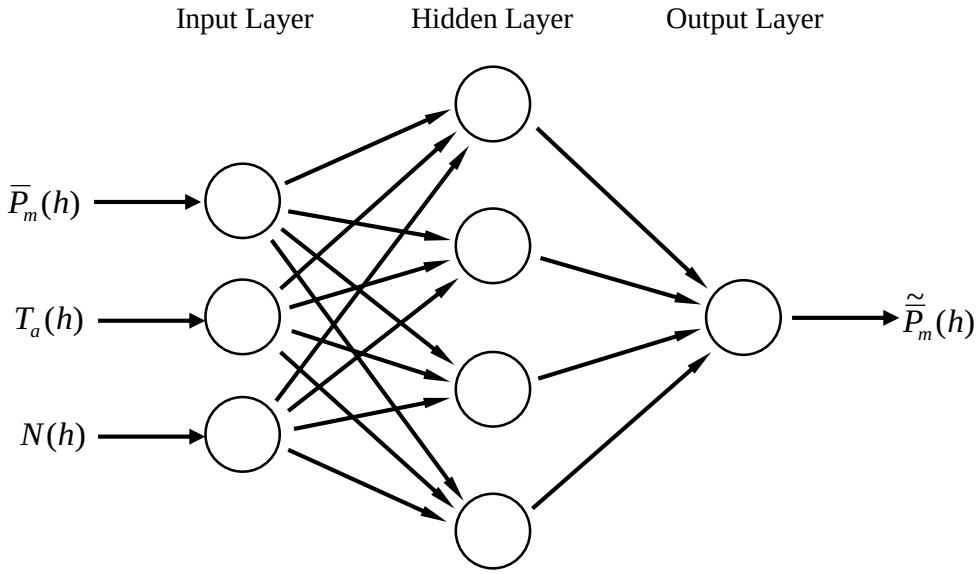

Figure 4. Diagram of the Artificial Neural Network configuration

b. Multivariate Polynomial Model

The polynomial models are very popular due to their simplicity in form, their well-known and understood properties and their flexibility of shapes. Moreover, they are computationally easy to use. For these reasons, there are many applications of these models in the forecasting in general, and in PV production forecasting in particular (Dazhi, 2012), (IEA, 2008).

However, as the model takes into account only one input variable, the precision of forecast is limited and therefore the Artificial Neural Network model becomes the most applied model in

this field (Pedro & Coimbra, 2012). In this paper, a Multivariate Polynomial Model, which takes into account several input variables is proposed to improve the accuracy of the prediction of PV output power.

The output prediction of the normalized value at time (h+1) is a multivariate polynomial function of the input variables:

$$\begin{aligned}\tilde{\overline{P}}_m(h+1) &= b_1.\overline{P}_m(h).N(h).T_a(h) + b_2.\overline{P}_m(h).N(h) + b_3.\overline{P}_m(h).T_a(h) + b_4.N(h).T_a(h) \\ &+ b_5.\overline{P}_m(h) + b_6 N(h) + b_7 T_a(h) + b_8\end{aligned} \tag{8}$$

The coefficients of the multivariate polynomial function are estimated from the historical data using the Levenberg-Marquardt nonlinear least squares algorithm (Seber & Wild., 2003). This algorithm allows to determine the set of parameters b giving the minimal squares of the deviations:

$$S(b) = \sum_{h=1}^{M}\left[\overline{P}_m(h) - \tilde{\overline{P}}_m(h)\right]^2 \tag{9}$$

c. <u>Persistence Model</u>

The persistence model is based on a simple rule: the output value of the predicted variable at (h+1) is equal to its value at (h). The advantage of this technique is that it does not need to be trained by a series of historical data, however the accuracy of the forecast is not high.

In this paper, the Scaled Persistence Model is applied in order to reduce the forecasting error. This model is applied on the normalized value:

$$\tilde{\overline{P}}_m(h+1) = \overline{P}_m(h) \tag{10}$$

4. Results

In this section, we will analyze the influence of the duration of training data on the forecasting error. The parameters of the forecast model (Artificial Neural Network and Multivariate Polynomial Model) will be estimated using the historical data in 30 days, 60 days, 90 days, 180 days, 270 days and 365 days. Then, the model will be tested on a duration of 331 days (Guadeloupe) and 308 days (Lille). Due to its characteristic, the Scaled Persistence Model does not require any historical data, therefore, it will be tested directly with the testing data.

4.1 Case of Guadeloupe

The Table 1 and the Figure 5 show the evolution of the forecast error with different training duration in Guadeloupe.

Table 1. The evolution of the forecast error with different training duration (Guadeloupe)

NMBE			
Duration of training data	Artificial Neural Network	Multivariate Polynomial Model	Scaled Persistence Model
30days x 10 samples	1.74%	-0.87%	0.79%
60days x 10 samples	0.22%	-1.41%	
90days x 10 samples	-0.62%	-0.61%	
180days x 10 samples	-0.30%	-0.34%	
270days x 10 samples	0.27%	0.27%	
365days x 10 samples	0.67%	0.60%	
NMAE			
30days x 10 samples	9.90%	10.06%	9.60%
60days x 10 samples	9.32%	9.51%	
90days x 10 samples	9.23%	9.26%	
180days x 10 samples	9.13%	9.21%	
270days x 10 samples	9.07%	9.10%	
365days x 10 samples	9.22%	9.19%	
NRMSE			

30days x 10 samples	13.22%	13.00%	13.07%
60days x 10 samples	12.36%	12.21%	
90days x 10 samples	12.15%	11.97%	
180days x 10 samples	11.95%	11.94%	
270days x 10 samples	11.90%	11.86%	
365days x 10 samples	12.09%	11.93%	

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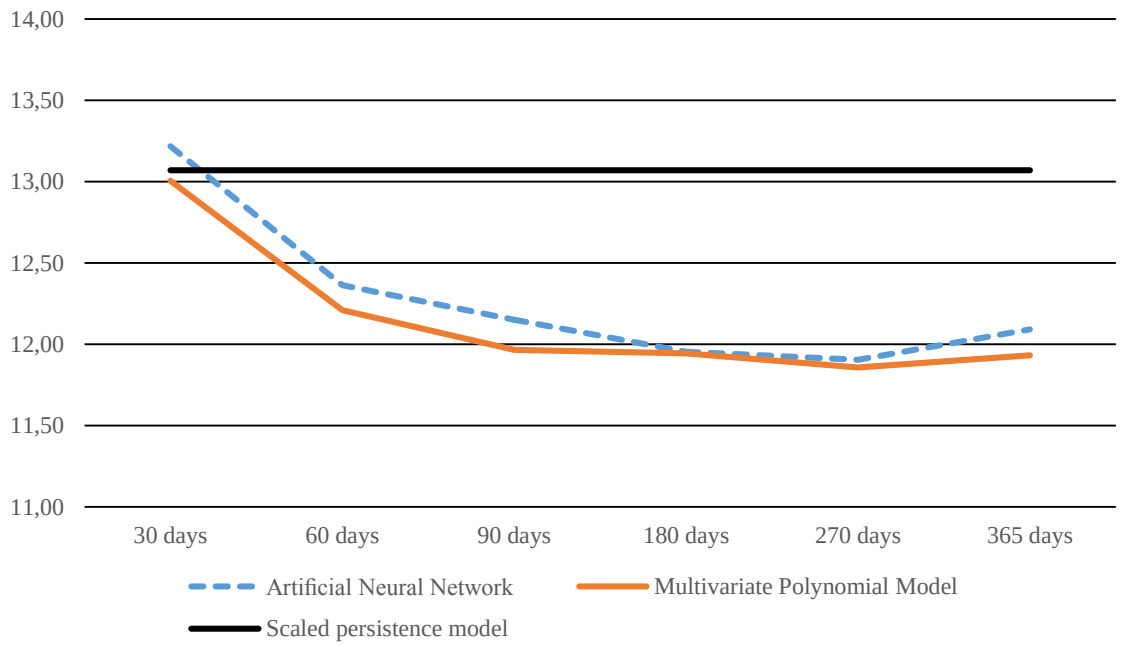

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194 Figure 5. The evolution of the NRMSE (%) with different training duration (Guadeloupe)

195 The value of the bias error NMBE allows to evaluate the tendency of the prediction model to
196 underestimate or overestimate the PV output power. In this study, the NMBE is relatively small
197 with all 3 methods and oscillating around the zero. However, the variation of the NMBE does
198 not follow any certain rule (Table 1).

199 The NMAE is used to measure how close the forecasts or predictions are to the eventual
200 outcomes. As presented in the Table 1, from the training data of more than 1 month, the NMAE
201 of the Artificial Neural Network and the Multivariate Polynomial Model is lower than the

Scaled Persistence Model. The NMAE of the Multivariate Polynomial Model is slightly higher than that of the Artificial Neural Network.

The Root-Mean-Square Error (RMSE) is a frequently used measure of the differences between value (Sample and population values) predicted by a model or an estimator and the values actually observed. Basically, the RMSE represents the sample standard deviation of the differences between predicted values and observed values. The NRMSE is the RMSE divided by the range of observed values of the variable being predicted. In literature, the NRMSE is mostly preferred than the NMAE because this indicator contain both information of the bias and the variance of the prediction.

As the Scaled Persistence Model does not require the historical data, the forecasting error of this model is usually the highest among the three. However, it is still lower than the forecasting error of Artificial Neural Network with only 1 month of training data. Generally, if the duration of the collected data is shorter than 1 month, it is advisable to use the Scaled Persistence Model. From more than one month of training data, the Artificial Neural Network and the Multivariate Polynomial Model are more accurate. The forecasting error reduce rapidly from more than 13% to less than 12% with the training data of 3 months (Multivariate Polynomial Model) or of 6 months (Artificial Neural Network). With the Multivariate Polynomial Model, the difference of forecast error between the training duration of 3 months, 6 months, 9 months and 1 year in Guadeloupe is negligible. The training period can be considered as sufficient after 3 months of data collection.

With the training data of 365 days, the forecast error is slightly higher than that given by the training data of 270 days, which is not coincident with the tendency of reduction of the forecast error with longer training data. This contradiction could be explained by a hypothesis that the training data of the period of 3 months which has just been added to the training data may disturb the forecast model. To verify this hypothesis, another forecast is implemented using the

training data from the first 9 months of the training year (see Figure 1). The result shows that the forecast error in both models is higher than that using the training data from the last 9 months (12.21% with Artificial Neural Network and 12.01% with Multivariate Polynomial Model). Therefore, the hypothesis can be confirmed.

4.2 Case of Lille

The Table 2 and the Figure 6 show the evolution of the forecast error with different training duration in Lille.

Apart from the Scaled Persistence Model, which does not require the historical data, the forecast error of the Artificial Neural Network and the Multivariate Polynomial Model is high with the training data from 1 to 3 months due to the seasonal effect of Lille. With this effect, the right parameters of the forecast model cannot be evaluate from the training data of 1 to 3 months. However, from 6 months and above, the forecast error is reduced significantly (from 12.71% to 10.69% with Multivariate Polynomial Model). The reduction starts from 6 months of training data, not from 1 year, due to the symmetry of the PV production of Lille in a year (see Figure 2). The difference of forecast error between the training duration of 6 months, 9 months and 1 year in Lille is negligible. The training period could be finished after 6 months of data collection.

Table 2. The evolution of the forecast error with different training duration (Lille)

NMBE			
Duration of training data	Artificial Neural Network	Multivariate Polynomial Model	Scaled Persistence Model
30days x 10 samples	-5.62%	-7.65%	-0.09%
60days x 10 samples	-9.35%	-6.78%	
90days x 10 samples	-4.45%	-4.08%	
180days x 10 samples	-0.24%	-0.23%	

270days x 10 samples	-0.73%	-0.81%	
365days x 10 samples	-0.76%	-0.81%	
NMAE			
30days x 10 samples	13.02%	11.43%	7.44%
60days x 10 samples	12.17%	10.90%	
90days x 10 samples	10.54%	9.36%	
180days x 10 samples	7.63%	7.62%	
270days x 10 samples	7.65%	7.71%	
365days x 10 samples	7.62%	7.75%	
NRMSE			
30days x 10 samples	18.39%	16.21%	11.37%
60days x 10 samples	16.07%	15.34%	
90days x 10 samples	14.79%	12.71%	
180days x 10 samples	10.83%	10.69%	
270days x 10 samples	10.62%	10.63%	
365days x 10 samples	10.53%	10.63%	

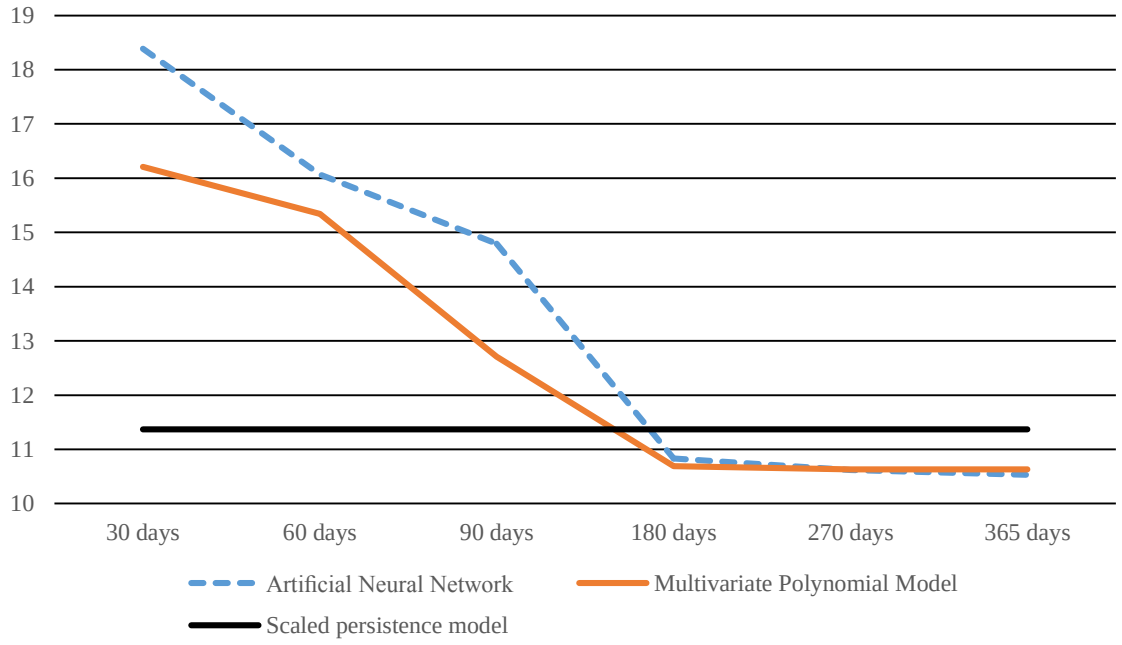

Figure 6. The evolution of the NRMSE (%) with different training duration (Lille)

We can observe that the duration of data collection required to have a good forecast in Lille is higher than the duration of data collection needed in Guadeloupe (6 months compared to 3 months). However, the forecast error in Lille is smaller (10.69% compared to 11.97%).

4.3 Analysis and recommendations

Among the 3 models, the Scaled Persistence Model does not require the historical data, therefore the forecast can be obtained directly without training period. However, the quality of forecast is not high. In the beginning, this model can compete with the others 2 forecast models but from 2 months of training data (Guadeloupe) and from 6 months of training data (Lille), the quality of the forecast by these model is much better than that of the Scaled Persistence Model.

The Artificial Neural Network and the Multivariate Polynomial Model have the same evolution of forecast error due to the fact that both of these models use the Levenberg-Marquardt algorithm as core learning technique. The Multivariate Polynomial Model has a better forecast quality than the Artificial Neural Network. In Guadeloupe, the Artificial Neural Network needs 6 months of training data to acquire the forecast error lower than 12% while the Multivariate Polynomial Model needs only 3 months to go under this level. Another advantage of the Multivariate Polynomial Model is the simplicity and the transparency of the model. This is an analytical model, it means that the relation between the predicted value and the input variables can be represented in the form of an equation, different from the Artificial Neural Network, where this relation can only be represented by a black box.

As presented in the Figure 1 and the Figure 2, the PV production of Guadeloupe and Lille has very different characteristics. In Lille, there is a seasonal effect that there is not in Guadeloupe. However the PV production of Lille is less fluctuant than that of Guadeloupe. Therefore, to obtain a good quality forecast, the model of Lille needs a longer duration of training data (6

months instead of 3 months). But once the model is trained, it provides a better performance than that of Guadeloupe.

5. Conclusions

This paper focus on the necessary duration of data collection to have a quality forecast of PV production for two climatic conditions: a temperate and a tropical weather conditions. In order to investigate this issue, the study is implemented on 2 PV installations: the first one in Guadeloupe, the second in Lille; using 3 different forecast models: the Scaled Persistence Model, the Artificial Neural Network and the Multivariate Polynomial Model.

The results show that with the temperate climate such as Lille, where the seasonal effect existed, a training duration of at least 6 months is needed to acquire a high accuracy forecast for PV generation instead of 3 months with the tropical climate at Guadeloupe. However, once the model is trained, the performance is better (error of 10.69% at Lille compared to 11.97% at Guadeloupe).

This research proposes to use the Scaled Persistence Model to forecast the PV output power during the data collection as this model does not require the historical data. Once the data collection phase is finished, the Multivariate Polynomial Model could be applied in order to provide a better accuracy. With the application of PV output forecast, the exploitation of PV becomes more efficient, reducing the risk of power outages and improving the reliability of power supply.

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