A model for temporal variations in the output of solar PV power plants

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Abstract— The intermittent nature of photovoltaic power can induce serious challenges in grid management and operation when large capacities of photovoltaics are integrated within the grid in a given region.

The Wavelet transform-based Method presents itself as a way to simulate the variable average irradiance on an area with high PV penetration. The basis of this method is applying the wavelet transform to decompose the normalized irradiance signal, obtained from the measured irradiance at single point sensor, into wavelet discrete modes at different timescales. Then, by combining it with the concept of Variability Reduction (VR) it is possible to upscale the wavelet modes from that single sensor to simulate the wavelet modes of the entire site.

To validate this method, two approaches were used to study in detail the proximity between the model average irradiance and the actual irradiance. The first approach is studying the power content (Fpis) of the irradiance signal at each timescale. This guarantees the distribution of power into frequency components is the same in both irradiance profiles. The second approach is by studying the irradiance deviation patterns (RRs) of each signal at a chosen time-interval. The irradiance of the single point sensor will be included for the analysis to see the improvement when using this method.

Fast irradiance changes prove to be hazardous for PV grid-connected solar parks with sharp voltage and reactive power variations that may jeopardize future PV integration into the electrical grid.

Keywords— Photovoltaic, Solar intermittency, WTM, Ramp Rates, Geographic smoothing, Grid integration

I. INTRODUCTION

The role of grid-connected photovoltaic power system is gradually becoming more significant as an electric supply source and as an integral part of the electrical grid. With this upsurging in PV generating energy it leads to a growing concern about the PV output variability having a negative effect on utility grid stability which poses some notable challenges to grid engineers, planners and operators. As a result, intermittency of solar power is a crucial driver in the growing costs for the integration of PV systems into the electric grid because supplementary system resources are essential to preserve the grid’s reliability. To accurately validate a model that produces realistic results of unpredictable fluctuations related with cloud movements, several points of interest over an area with high PV penetration have to be chosen and a huge amount of solar data has to be collected at those points. To the purpose of solar energy applications, the current literature is very limited on the topic of solar irradiance variability at the regional or continental scale. Thus, one of the main problems when modelling solar intermittency is the lack of available solar data in a specific location, especially for high-frequency data. The main objective of the present work is to implement a suitable model that can be used to describe and simulate spatial-temporal variations in solar radiation and study its impact for high PV penetration local areas using only one pyranometer sensor. The chosen model is to be implemented at Oahu Solar Measurement Network with one-second measurement irradiance data for two different days, containing at least some solar variability. The last goal of this thesis is to understand the fast voltage variations during cloud transients in the distribution system and discuss solutions to mitigate those variations. This document is organized as follows:

- **Chapter 2 (Background)** provides the necessary background information and the state of the art related work;
- **Chapter 3 (WTM Algorithm)** presents a detailed explanation step by step of the chosen model (Wavelet transform-based Method (WTM)), i.e. explaining how by only using a single irradiance point it is possible to simulate the average irradiance of an entire network of modules or sensors;
- **Chapter 4 (Testing and Validating WTM)** focuses on implementing this method in Oahu Solar Measurement Network using irradiance measurements at the site. Then, validating this method by comparing the output irradiance of the model with the actual irradiance across the network of sensors. It is expected to see the improvement when comparing to the irradiance measurements of the single point sensor;
- **Chapter 5 (Voltage variation due to solar PV in the distribution grid)** presents a detailed analysis on the impact of fast solar fluctuations on the PV voltage and other components connecting the PV array to the distribution grid. A brief explanation of several solutions is given to mitigate such issues and facilitate large quantities of PV penetration in the future;
- **Chapter 6 (Conclusions)** draws the conclusions and presents future developments to be done on the subject;
II. BACKGROUND

The classification of the solar resource is frequently considered only in terms of magnitude, how much solar energy is available at a given local of interest over a specific time period. Nonetheless, a comprehensive classification of this resource must include the variability of available solar irradiance over time, whether it is on the scale of one second to the next, one day to the next, one season to the next, or even one decade to the next. It is also possible to consider changeability of the solar resource in spatial-temporal manner, i.e. how it varies over distance and timescale of the solar fluctuations.

A. Identically Distributed Blocks Method

The first and simpler approach presented here to model solar variability was proposed by Kato et al. (2011) [1] and estimates the standard deviation of the total power output variation of high penetration photovoltaic system spread over a large area.

![Figure 1 Area with subgroups of N blocks](image)

The area to be studied will be divided into sub-groups and each subgroup is divided into N equally sized blocks, as shown in Figure 1. In [1] the authors found out that for independent sites the solar variability over the entire area tends to the multiplicative inverse of the total number of modules ($1/\sqrt{N}$).

B. Dispersion Factor Method

The Dispersion Factor Method was developed by Hoff and Perez (2010) [2] with the goal to rigorously quantify power output variability from an ensemble of PV Systems ranging from a single central station to an entire fleet. In this method, a fleet is considered to be a group of N equally spread out and identical PV systems. For this method, the authors define two important variables output variability of a fleet ($\sigma_{\text{foot}}$) and the Dispersion factor (D).

![Figure 2 Relative Output Variability as function of the Dispersion Factor](image)

Combining the Dispersion Factor concept with the expression for the output variability, it is possible to establish four different regions in this method (Figure 2):

1. **Spacious Region:** The first region to be considered is when the PV systems are so dispersed that it is possible to assume that for any PV system, the output variability can be considered independent from each other ($\sigma_{\text{foot}} = \sigma_{\text{local}}/\sqrt{N}$).

2. **Limited region:** For this region, the PV systems are still dispersed from each other but not as dispersed as the Spacious region ($\sigma_{\text{foot}} < \sigma_{\text{local}}/\sqrt{N}$).

3. **Optimal point:** In this region, the cloud disturbance affects the next PV system immediately after cloud reaches the end of the previous PV system in one-time interval ($\sigma_{\text{foot}} = \sigma_{\text{local}}/N$).

4. **Crowded Region:** Lastly, one has to consider the case where the cloud disturbance affects more than one PV system in one-time interval ($\sigma_{\text{foot}} = \sigma_{\text{local}}/D$).

C. Wavelet transform-based Method

The third and last method to be treated here, the Wavelet transform-based Method, was developed by Lave et al. (2011) [3] to simulate the power output on a large area with high PV penetration. The basis of this method is applying the wavelet transform to decompose the normalized irradiance signal, obtained from the measured irradiance at a single point sensor, into wavelet discrete modes at different timescales. Then by combining it with the concept of Variability Reduction (VR) (to be discussed later) it is possible to upscale the wavelet modes from that single sensor to simulate the wavelet modes of the entire fleet of PV modules.
D. Comparison between methods

The first methods, Identically Distributed Blocks, does not considers the timescale of the solar fluctuations, thus this lack of information makes it the most incomplete method of the three. The Dispersion Factor method requires readings of all the N systems of the entire PV fleet. This means obtaining solar data for many different locations, which is sometimes difficult or even impossible if the PV fleet is too large. The wavelet-based method being an upscaling method has a lead over the other two methods since the solar irradiance data only needs to be collected from a pyranometer sensor when the scaling factor A is known, i.e. only the cloud speed is required at the given location. Thus, WTM significantly reduces the data requirements to use on the algorithm.

III. WTM ALGORITHM

The Wavelet transform-based Method algorithm will require the following inputs: 1) Sensor’s Latitude, Longitude and Altitude; 2) Sensor’s tilt and azimuth angles; Sensor’s time stamps (usually in the order of seconds or minutes); 3) Global Horizontal Irradiance (GHI) time-series from a single point sensor; 4) Day of the Year (DoY); 5) Local time; 6) Local Standard Time Meridian (LSTM); 7) Mapping all sites; 8) Daily Cloud speed information

A. Clear-Sky Model

The model proposed by Ineichen and Perez (2002) [4] was used as a clear-sky model to compute the clear sky irradiance. The inputs for this model are air mass (AM), Linke Turbidity (TL), elevation (h), the extra-terrestrial radiation and the zenith angle (complementary to the solar elevation angle):

\[
GHI_{\text{Clear}} = a_i \times I_0 \times \cos(z) \times e^{-a_2 \cdot AM \cdot (F_{1t} + F_{1z} \cdot (TL - 1))}
\]  

(3.1)

Where:

\[
F_{1t} = e^{-\frac{h}{1000}} \\
F_{1z} = e^{-\frac{h}{1350}} \\
a_1 = 5.09 \times 10^{-5} \times h + 0.868 \\
a_2 = 3.92 \times 10^{-5} \times h + 0.0387
\]  

(3.2)

B. Wavelet Decomposition

The next step is the application of the discrete wavelet transform (wavelet transform for which the wavelets are discretely sampled) to the solar-irradiance times series obtained in equation (3.1), given by the following equation:

\[
w_i(t) = \sum_{t'=t_{\text{start}}}^{t_{\text{end}}} K_i \left( t' \right) \left( \frac{1}{\sqrt{t}} \right) \cdot \left( t' - \frac{t}{t} \right)
\]  

(3.3)

Where the timescale (duration of the fluctuations) is \( t \), \( t_{\text{start}} \) and \( t_{\text{end}} \) designate the start and the end of the normalized irradiance time series respectively (e.g. sunrise and sunset) and \( t' \) is a variable of summation.

C. Spatial-Temporal Correlations and Coefficient “A”

Estimating the correlation between wavelet modes across the power plant is the most important step of this method. The reason why this coefficient \( \rho(d_{m,n}, i) \), is of great importance is linked with the best aspect of using this method, which is collecting irradiance data from only one-point sensor to simulate the power output of a PV power plant.

The correlation between sites varies with distance between them and with the timescale as shown in Table 1.

<table>
<thead>
<tr>
<th>Distance between pairs of sites</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timescale of the fluctuations</td>
<td></td>
</tr>
</tbody>
</table>

Inclusively, the scaling coefficient ‘A’ directly proportional to the cloud’s speed \( A = \frac{1}{2CS[m/s]} \) [4]. Thus, the correlation coefficient is given by the following expression:

\[
\rho(d_{m,n}, i) = \exp\left( -\frac{d_{m,n}}{A \cdot i} \right) \\
\rho(d_{m,n}, i) = \exp\left( -\frac{1}{0.5 \cdot \text{CS} \cdot i} \right)
\]  

(3.4)

D. Variability Reduction

The Variability Reduction is nothing more than the ratio of the variance of the normalized irradiance at the single point sensor and the variance of the average of the entire power plant footprint, given by:

\[
VR(i) = \frac{N^2}{\sum_{m=1}^{N} \sum_{n=1}^{N} \rho(d_{m,n}, i)}
\]  

(3.5)

By acknowledging that the distance between sites is a parameter does never change, VR will only depend on two variables: timescale and the correlation scaling coefficient “A”.

1) First, within the same day, the larger timescales the faster VR will tend to 1. The logic behind it, is that the longer the fluctuations are, the more likely it will approach the case where the variations that pass through the sensor will almost be the same as an average of the fluctuations of all sites. On the contrary, short timescales fluctuations will cause rapid variations in the sensor and therefore are not a good representation of the average fluctuations that occur over all
PV modules. Inclusively, if the modules are well dispersed enough, short-term fluctuations will be strongly damped by geographic smoothing.

2) Secondly, dependence on the coefficient “A” is as follows: smaller values of “A” (sites weakly correlated) will lead to higher values of VR and higher values of “A” (sites strongly correlated) means VR will approach 1.

E. Simulated Wavelet Modes and Irradiance

Combining the wavelet modes (from step 1) at each time scale with the VR for the same timescale, we obtain the averaged simulated wavelet modes of all sites:

\[ W_{i}^{sim}(t) = \frac{w_{i}(t)}{\sqrt{VR(t)}} \tag{3.6} \]

To obtain the simulated Clear-Sky Index, we do the inverse of the wavelet transform (sum of all the simulated wavelet modes) to obtain the reconstructed signal:

\[ K_{i}^{sim}(t) = \sum_{t=1}^{t=12} W_{i}^{sim}(t) \tag{3.7} \]

The final step is to 'denormalize' the simulated irradiance by multiplying again by the Clear-Sky irradiance:

\[ GHI(t)^{sim} = K_{i}^{sim} \times GHI_{clear}(t) \tag{3.8} \]

IV. TESTING AND VALIDATING THE WTM

The main focus of this chapter is testing and validating the WTM. This is accomplished if we can obtain the average irradiance of a network of sensors by just using the measured irradiance signal of a single point sensor. To properly validate this model, the authors use two approaches to prove that the simulated areal-irradiance can be compared to the actual irradiance average of all available sensors. The first approach is studying the power content of the irradiance signal at each timescale. This guarantees the distribution of power into frequency components is the same in both irradiance profiles. The second approach is by studying the irradiance deviation patterns of each signal at a chosen time-interval. If the deviation pattern is the identical for the two previously mentioned signals, it tells us that these GHI profiles will have similar solar variability distribution.

Thus, this method will be tested at a distributed sensor system owned by the National Renewable Energy Laboratory (NREL), located in Oahu, Hawaii, USA. This area is considered by the NREL as one of the top zones with strong intermittency, making it a perfect site to test the Wavelet transform-based Method. The solar measurement grid facility consists of 17 global horizontal irradiance sensors, spread across an approximately 1 km² and with 1 reading per second, as shown in Figure 4.

A. Correlation between sites

An important input for the WTM is the correlation between sites. For the two days of interest, 4 sensors (DHHL3, DHHL4, DHHL5, DHHL10) of the Oahu solar sensor’s network were used to compute the scaling coefficient ‘A’.

After mapping all the coordinates for all sites, computing the distances between each other can be done by using the Haversine formula. For any two points on a sphere, the haversine formula is given by:

\[ d_{op} = 2R \arcsin \left( \sin \left( \frac{\text{Lat}_2 - \text{Lat}_1}{2} \right) \right) \tag{4.2} \]

In both Figure 5 and Figure 6, the blue dots represent the correlation between all pairs of the four chosen sensors for every timescale. The red dashed line represents the best fit to the relationship in equation (4.2). As shown in Figure 5, the exponential constant B=0.4001, meaning the scaling coefficient should be equal to 2.5. For December 2nd, the exponential constant B=0.2152. Thus, the scaling coefficient for this day is around 4.6. This conveys the idea that December 2nd is more highly correlated. Changes in irradiance on a single point sensor are much closer to the same changes in irradiance of all sensors, when compared to October 31st.
Since ‘A’ is the only variable parameter, one can expect that for October 31st (with smaller ‘A’-value) it will lead to more geographic smoothing across the Oahu Solar Measurement Network.

Table 2 Daily correlation scaling coefficients

<table>
<thead>
<tr>
<th>“A” value (m/s)</th>
<th>Cloud Speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>October 31st</td>
<td>2.5</td>
</tr>
<tr>
<td>December 2nd</td>
<td>4.6</td>
</tr>
</tbody>
</table>

B. Validating the WTM

In this subchapter, we will particularly focus on short timescale (from 2s to 64s) because, as stated before, the WTM has a bigger impact on abrupt and fast changes in the irradiance profile. Thus, periods of time with longer timescales are less relevant for this method. Furthermore, to prove this model, we are not interested to see how the daily profile changes over a day, but the smoothing that occurs at those short-term fluctuations. This is particularly related to the concept of Variability reduction (see section III.D). Shorter timescales will have larger values of VR and for longer timescales, this value will tend to 1.

It is worth noticing, that the results from Figure 5 and Figure 6 are congruent with the variability reduction obtained in Figure 4.6. For both test days, the variability reduction starts with a value of practically 14, which is the number of sensors used for this analysis \( VR(t) = N \).

As previously mentioned, Lave et al. (2011 [3]) used two approaches to validate their model and accurately quantify the solar variability at each timescale.

First, the Fluctuation power index can be used to compare the power content of wavelet modes at each timescale. The power content of a signal refers to the spectral energy distribution that would be found per unit time, in this case, time intervals of timescales will be considered.

The following expression was used to compute the power content at each timescale for each signal:

\[
Fpi_{signal}(i) = \frac{1}{T} \int \left| w_i(t) \right|^2 dt
\]

(4.3)

Where \( T \) is equal to 86400 and represents the period of time under consideration (number of seconds in one day).

As anticipated, Figure 7 and Figure 8 show a strong agreement at short timescales for the Fpis WTM and Fpi average of all sensors. The match is almost perfect for December 2nd and for October 31st overlaps well with a small deviation on timescales 8 and 16 seconds. This means that the high frequency content of the actual average irradiance signal is approximately the same as the predicted by the model. The Fpis can also confirm that the solar intermittency that occur at shorter timescales are the ones that are most reduced due to geographic smoothing. Fluctuations longer than 512 secs (around 8.5 mins) for December 2nd, practically do not benefit from the smoothing effect. At those timescales, all three Fpis start to line up, meaning the power content of each signal is about the same. For October 31st, the smoothing effect starts to get weaker around 1024 secs (around 17 mins).
The second method used by the authors to validate the model is called Ramp Rates (RRs). Instead of measuring the power content at each timescale, Ramp Rates measure the irradiance deviation patterns of each signal at each time period of choice.

The Ramp Rates will be computed with the following expression:

$$\begin{align*}
RR_{\text{DHHL3 irradiance}}(t) &= \frac{1}{\Delta t} \left( I(t)^{+\Delta t} - I(t)^{-\Delta t} \right) \\
RR_{\text{WTM irradiance}}(t) &= \frac{1}{\Delta t} \left( I(t)^{+\Delta t} - I(t)^{-\Delta t} \right) \\
RR_{\text{Excel irradiance}}(t) &= \frac{1}{\Delta t} \left( I(t)^{+\Delta t} - I(t)^{-\Delta t} \right)
\end{align*}$$

(4.4)

The ramp rate can be calculated by finding the difference between all the adjacent points of three irradiance profiles, with a variable time-interval of interest. The abscissa axis (xx) of Figure 9 and Figure 10 represent the absolute value of the Ramp Rates in percentage. In other words, the portion of irradiance that increases from one time-interval to another. The RRs plots should be interpreted as follows: for example, if the Ramp Rate is about 10, this means that between one time-interval the irradiance increases about 10%. Likewise, if the Ramp Rates have negative values, it means the irradiance decreases a certain amount on that interval.

As a final analysis, we observe that both Figure 11 and Figure 12 are also consistent with the results obtained so far. The upper part of Figure 11 and Figure 12 present the contrast between both DHHL3 measured irradiance profile and average irradiance of all sensors irradiance profile for the two test days. On the other hand, the bottom part of the same two figures illustrate the improvement from the single point sensor, when compared to the simulated irradiance.

Figure 9 and Figure 10 contain information concerning the extreme Ramp Rates of solar variability for four short-timescales chosen on October 31st and December 2nd respectively. The 1-sec graphs on the top-left side represent the Ramp Rates for the original signals, whereas the remaining graphs symbolize the Ramp Rates of the same signal but with irradiance averages of 15 secs, 30s and 1 min.

Two important conclusions are possible to withdraw from Figure 9 and Figure 10:

1) The extreme ramp rates are much weaker for the RRs Average Excel and for the RRs WTM, when compared with the RRs of the DHHL3 sensor. From the cumulative distribution plots, it is evident that on each day the DHHL3 Sensor RRs are the widest and the most dispersed when compared to the other two. This indicates that the probability of large variations in the irradiance profile is more common for the DHHL3 Sensor rather than the actual average irradiance profile or the simulated irradiance profile. In all the four graphics, the cumulative distribution function for the actual and simulated irradiance RRs seem to overlap well showing that statistically, the model represents well the solar variability that occurs over that specific area. This proves that the actual average of the 14 sensors is much smoother than one single sensor.

2) With increasing timescales, the Ramp Rates of the actual average of all sensors (RR Excel) starts to get closer to the RR WTM. For instance, for the 1-min graphs in both figures, these two almost overlap. This means, if we would be interested on studying solar variability with another timestep, the model would present the same good results.

As a final analysis, we observe that both Figure 11 and Figure 12 are also consistent with the results obtained so far. The upper part of Figure 11 and Figure 12 present the contrast between both DHHL3 measured irradiance profile and average irradiance of all sensors irradiance profile for the two test days. On the other hand, the bottom part of the same two figures illustrate the improvement from the single point sensor, when compared to the simulated irradiance.
Meaning, if we look at the simulated irradiance and the actual average irradiance profile of all sensors, it is clearly evident that they have a better match when compared with the DHHL3 measured irradiance profile. These results, permit to have a general idea of the geographic smoothing that occurs at those short time fluctuations and the benefit of using the wavelet method to study the irradiance profile when considering a relatively large area.

From this RRs and the Fpis analysis it is possible to conclude that sensor measured irradiance can be a bad representation of the average irradiance across the solar park and by using it, it can lead to big errors on the PV power plant output for cloudy days. With this bad estimation, ways to control and minimize the impact of this intermittency on the grid may fail.

Based on results, the following points are noteworthy: 1) Smoothing of the irradiance profile across a solar park or any other area with large penetration of PV generation, would be possible by geographically distributing PV modules. 2) Irradiance data become uncorrelated as the distance between sites increases. 3) Sites that are uncorrelated will experience more smoothing effect and sites that are strongly correlated will not experience this smoothing at all.

The WTM proves to be an accurate model to simulate the solar variability of a PV power plant or any other large area with high PV penetration. It was found, as expected, that the exact magnitude of real-time irradiance fluctuations and the simulated irradiance fluctuations were not perfectly matched, although it showed a big improvement from the point sensor variability. Therefore, the measured at the single point sensor cannot be considered as true representative of the average irradiance across any area with high PV penetration. Nevertheless, this method serves its purpose which is to simulate the areal-irradiance over zones with high PV penetration that statistically has similar spatial-temporal variability distribution at different timescales as the actual irradiance over that area.

Although the RRs and Fpis results wind up as expected and evidenced the enhancement that exists from the point sensor irradiance to the modelled irradiance, there is major drawback when implementing this method. The downside of the model is directly linked with the algorithm itself. When structuring this method Lave et al. (2011) [3] [4] only include cloud size and the cloud speed and not the direction of the clouds movement. Therefore, it can create a slightly offset between the simulated irradiance (originated from the DHHL3 GHI measurement) and the actual average irradiance. Nevertheless, with the assumptions that typical cloud sizes are relatively larger when compared to the distances measured across the area of interest, the obtain results on this chapter prove that the accuracy of the WTM is almost independent of these geographic limitations.

To sum up, as PV generation expands with higher penetration within the distribution grid, it is imperative to understand the typical fluctuations on various timescales, as well as the potential for energy storage, PV array size, and geographic dispersion to mitigate these fluctuations. WTM presents itself as a valuable tool to study and predict the magnitude and occurrence of the actual extreme RRs for high PV integration on the grid.

V. VOLTAGE VARIATION DUE TO SOLAR PV IN THE DISTRIBUTION GRID

Since PV generation has no mechanical inertia, fast solar irradiance changes associated with cloud transients cause instantaneous variations in PV power output, resulting in rapid and possibly significant voltage changes in systems with high penetration of PV generators.

In this chapter we will mainly focus on the impact that rising demand for solar energy installation allied with its intermittent nature have on the voltage. For an area with high penetration of photovoltaic (PV) systems, voltage fluctuations can occur at the distribution systems, resulting in inverter tripping out (i.e. disconnecting the PV arrays) and insufficient power to meet the load. Undesirable voltage fluctuation problems may also affect the operation of the voltage regulating equipment and can induce some unwanted reactive power into the distribution electrical grid.
To study the implications of solar variability on the power grid management a generic 1 MW grid connected PV solar power plant on MATLAB Simulink is proposed (Figure 13). The model will be tested for hypothetical abrupt changes in solar irradiance in the order of seconds, more specifically, every 3 seconds a change occurs in the irradiance profile and all simulation presented will be confined to a 30 second interval.

A. Performance analysis on the PV power plant’s DC-side

For all the following simulations of the represented model in Figure 13, will be tested considering a typical module temperature of 45 °C. Figure 14 illustrates the response of the system following a sudden increase and decrease in irradiance (with all PV modules receiving the same irradiance) with the values [1, 0.3, 1, 0.2, 0.9, 0.6, 0.7, 1, 0.1] in (kW/m²) with the step of 3 secs until 30 secs.

Figure 14 shows that the amount of power produced by the PV arrays follows the pattern of irradiance. This is because the MPPT controllers, by adjusting the boost converter duty cycle, keep the PV generating units operating point at their maximum power point despite the large fluctuations in irradiance that take place over the 30 seconds time frame considered. In the P&O algorithm perturbation in voltage will lead to a change in the power output. If at this disturbance an increasing voltage leads to an increasing power, it means that the operating point is at a lower voltage than the \( V_{mpp} \) and therefore the MPPT should increase the voltage towards the MPP. On the other hand, if an increasing voltage leads to a decreasing power, then the operating point is at higher voltages than the \( V_{mpp} \) and thus therefore the MPPT should decrease the voltage towards the MPP until it converges at the MPP.

Figure 15 shows the DC voltage after the DC-DC boost converter, i.e. at the input of the inverter. The red line represents the desired DC 500 V and the blue line represents the actual DC voltage with the fluctuations due to the rapid changes in irradiance. This figure shows that the MPPT itself cannot mitigate all the voltage fluctuations at the inverter’s input when trying to find a new MPP for irradiance changes.

B. Performance analysis on the AC-side

The MATLAB Simulink voltage source inverter uses the pulse width modulation (PWM).

The modulation process is done in a way so that the current and the grid voltage will be at same frequency and in the same phase with each other (i.e. power factor equal to 1). To measure the ability of an inverter using the PWM method to deliver AC power, the term modulation index is defined:

\[
m = \frac{V_{L-L}/AC}{\sqrt{3}} \quad \frac{V_{DC}}{2}
\]  

(5.1)

Figure 16 shows the modulation index for inverter with pulse width modulation (PWM).

By looking at Figure 16, it is perceptible these voltage fluctuations on the DC-side will affect the modulation process of the inverter and will cause a phase shift between the AC current and voltage. The result is a power factor different than one and inducing reactive power variations into the grid.

Figure 17 shows the output AC voltage, AC current and after the 1000-kVA 240V/30kV three-phase coupling...
transformer and in addition the injected active and reactive power into the electrical grid.

PV is a DC power source, meaning that there is no reactive power associated with PV itself. In order to control the active power to be injected in the grid, it can be done when a PV is connected to a load via a DC-DC converter, the DC voltage and DC current of the PV can be varied by the converter. As mentioned earlier, this is accomplished with a MPPT controller where the ideal case will be to extract the maximum active power. A DC-DC converter cannot inject or absorb any reactive power.

When an inverter is used to connect a PV DC power source with the grid, the only way to inject or absorb reactive into the grid, is if there is a phase shift between the current and voltage angles of the inverter.

Reactive power is directly proportional to the voltage, thus by comparing Figure 15 and Figure 18 it is easily to conclude that a sudden decrease in the voltage would lead to an unexpected reactive power absorption, likewise a sudden increase in the voltage would lead to injecting reactive power into the grid. Needless to say, that changes in solar irradiance allied with an increasing PV penetration on the grid will escalate this unexpected reactive absorption or injection problem on the distribution grid.

C. Minimizing voltage fluctuations due to irradiance changes at high PV penetration sites

There are significant technical challenges at every level associated with the grid integration of high penetration of solar photovoltaics. As mentioned before, these challenges are dependent on the timescale of changes in solar irradiance. This last section aims at briefly explaining different options that grid engineers, planners and operators may have at their disposal to tackle one of the main issues that is slowing down the integration of PV in the grid, i.e. solar variability.

To minimize transient voltage variations, solar park designers and engineers must adopt quick response solutions based on, for instance, reactive power (Var) compensation supplied by power electronic devices [6] or active power compensation provided by energy storage systems [7].

VI. CONCLUSIONS

A. Main Points

A significant increase in the penetration of PV generation and its intermittent nature could have a significant impact on the stability of the electrical grid. The presented master thesis focuses on implementing and testing the Wavelet transform-based Method, as a way to forecast the amount of solar variability at a given location. The key factor that makes the WTM more practical to be implemented than the other two existing methods is that the solar irradiance data only needs to be collected from a single pyranometer sensor. Therefore, at a given location and period of time the WTM algorithm has the ability to be run by only using numerical weather-forecast for cloud speed, the exact location of all modules and the irradiance from a single point sensor pyranometer. This irradiance measurements and the intermittency that occurs at the sensor will be representative of the cloud covering in the existing area.

This method was tested at a distributed sensor system owned by the National Renewable Energy Laboratory, located in Oahu, Hawaii, USA. This area is considered by the NREL as one of the top zones with sun intermittency, making it a perfect site to test the Wavelet transform-based Method. Two cloudy days were chosen from the available NREL’s 1-Year Archive dataset.

From the irradiance profile results it was obvious that the simulated area will average irradiance matched well with the actual average irradiance of all sensors. Nevertheless, to validate this last statement, two approaches were used. First, the Fluctuation power index can be used to compare the power content of wavelet modes at each timescale. The power content of a signal refers to the spectral energy distribution that would be found per unit time. The results showed a strong agreement at short timescales for the Fpis WTM and Fpi average of all sensors. This means that the high frequency content of the actual average irradiance signal is approximately the same as the predicted by the model. The second method to validate the model is called Ramp Rates (RRs). Instead of measuring the power content at each timescale, Ramp Rates measure the irradiance deviation patterns of each signal at each time period of choice. In this work we are only concerned with extreme Ramp Rates of solar variability at short timescales (1 sec, 15 secs, 30 secs, 1 min). The RRs results show that the extreme ramp rates are much weaker for the RRs Average Excel and for the RRs WTM, when compared with the RRs of the DHHL3 sensor. This indicates that the probability of large variations in the
irradiance profile is more common for the DHHL3 Sensor rather than the actual average irradiance profile or the simulated irradiance profile. For all the four timescales, the cumulative distribution function for the actual and simulated irradiance RRs seem to overlap well showing that statistically, the model represents well the solar variability that occurs over that specific area. This proves that the actual average of the 14 sensors is much smoother than one single sensor.

In the final chapter, the dynamic behaviour of large PV generation was studied for a generic 1 MW grid connected PV solar power plant. The aim of this model was to see how the several components of the grid connected solar park would react to fast changes in irradiance. It was observed that fast irradiance fluctuations contribute to deteriorated power quality, especially unwanted voltage variation on the DC side. While the solar inverter has long been the essential link between the photovoltaic generation and the electricity distribution network and converting DC to AC, it also the cause of unexpected reactive power oscillations on the grid.

The three main possibilities to tackle solar intermittency includes reactive power control methods, energy storage technologies and by geographically disperse PV generation on a given area.

B. Future work

There are still some points that can be explored to continue and possibly upgrade what was accomplished in the present work. A special case where there is space for improvement is at the correlation between sites function. Characterization of the “A” values used for the correlation between sites was computed generically with a cloud simulator, only considering cloud size and cloud speed, not including the direction of the clouds movement.

Possible future solar forecasting and variability algorithms may use ground-based sky camera to detect cloud motion and direction, as the broad field of view of the sky camera corresponds to the conventional observations of interest above the PV panels. These cameras can take ground-based whole sky images that can provide localized images of the sky of high temporal and spatial resolution, which allow for a detailed cloud observation.

For the purpose of this thesis, the benefits of an accurate cloud detection system, coupled with cloud motion estimates and cloud cover forecasts, can result on more accurate values of “A”.

Regarding the up surging in PV generating energy leading to a growing concern about the PV output variability having a negative effect on utility grid stability, this work only focuses on the voltage fluctuations and uncontrolled reactive power variations. Further work can tackle other issues by conducting full-blown grid reliability studies and cost-benefits analysis. Subjects such as other power quality problems (e.g. harmonic distortion), power flow control issues and frequency stability remain understudied.

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