



HAL
open science

On the Use of the Coefficient of Variation to measure Spatial and Temporal correlation of Global Solar Radiation

Rudy Calif, Ted Soubdhan

► **To cite this version:**

Rudy Calif, Ted Soubdhan. On the Use of the Coefficient of Variation to measure Spatial and Temporal correlation of Global Solar Radiation. *Renewable Energy*, 2014, pp.99-999. hal-01099045

HAL Id: hal-01099045

<https://hal.science/hal-01099045v1>

Submitted on 30 Dec 2014

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

25 **1.Introduction**

26

27 **1.1 Context**

28 Because of clouds, solar radiation is a fluctuating data especially under tropical climate. Indeed,
29 rapid changes in the local meteorological condition as observed in tropical climate can provoke large
30 variation of solar radiation. The amplitude of these variations can reach up to 700 W/m^2 . Moreover,
31 these solar radiation variations can occur within short time interval (from few seconds to few
32 minutes), depending on the clouds size, speed and number. The typical time scales associated with
33 these solar radiation variations also vary significantly with the geographical location.

34 Studies of solar energy systems are traditionally performed using daily or hourly data [1] [2]. These
35 data do not take into account the fluctuations mentioned previously. It has been shown that the
36 fractional time distribution for instantaneous radiation differs significantly from that obtained with
37 daily values.

38 Since solar energy systems are sensitive to instantaneous radiation fluctuations, simulations of
39 these systems with daily or hourly data can lead to significant error especially under tropical climate.
40 Indeed rapid variation of solar energy induces rapid and large variation of the output of such
41 systems. For example solar cells (photovoltaics), used for electrical production, have very short
42 response time and their electrical output will follow almost instantaneously the variations of solar
43 radiation.

44 With a high density of photovoltaics generation in a power distribution grid, rapid fluctuations of
45 the produced electrical power can lead to unpredictable variations of node voltage and power. In
46 small grids as they exist on islands (such a Guadeloupe, FWI) such fluctuations can cause instabilities
47 in case of intermediate power shortages with insufficient back-up capacity available. To manage the
48 electrical network and the alternative power sources requires a better identification of these small

49 time scales variations. This stresses the need for power system operators to develop real time
50 estimation tools for such disturbances.

51 Over the last years, some work were dedicated in establishing correlation between sites as a
52 function of distance [3] and in parameterization of short term irradiance variability [4]. There has
53 been resurgent interest in modeling and quantifying sub-hourly variability using different methods
54 and metrics. In [4] the authors uses and frequency analysis based on spectral and coherence
55 functions. This study showed high correlation for time scale greater than 3 hours :24h, 12h , 6h and
56 4h which are the main component in the irradiance signal.

57 Other studies have quantified the solar radiation variability with a prediction goal. Methods such as
58 wavelets [6], fractal parameters [7], [8] or hybrid models [9] were used for a given site.

59 The Marquez formula [10] is also used to measure the variability, it is defined with the variation of
60 the clear sky index CSI, $diff = CSI(t) - CSI(t - 1)$ and $V = \sqrt{mean(diff^2)}$.

61 An extension of this metric (called P) proposed by Perez et al. [5] is based on the dispersion of the
62 quantity $diff P = std(diff)$. Four metrics are used to characterize intra-hourly variability, including
63 the standard deviation of the global irradiance clear sky index, and the mean index change from one
64 time interval to the next, as well as the maximum and standard deviation of the latter. Different
65 time scales are studied from 20 seconds to 15 minutes.

66 In the present work we compare and analyze the statistical moments of the solar radiation
67 parameters measured at two sites in the Guadeloupean archipelago with a time step of one second.
68 We have established a correlation model for the coefficient of variation defined over a ten minutes
69 period.

70 The paper is organized as follow: the theoretical frame is exposed in section 2,

71 This model can be useful in choosing new sites of production not only for establishing correlation
72 from on site to another, but also in optimizing the geographical distribution of the solar farms within
73 the territory to favor a smoothing of the overall available solar electricity production. Indeed this
74 choice should be done not only on the basis of the annual potentiality of a site but also from the
75 stability of its production.

76 **1.2 Methodology**

77 In the present work, we compare and analyze the solar global radiation signals G_1 , G_2 , measured at
78 two sites in the Guadeloupean Archipelago. This study put in evidence the existence of a dynamical
79 correlation between G_1 and G_2 . To do so, we calculate for each signal, the global solar radiation
80 fluctuation $G'_{[T_1; T_2]}$ for time scales $T= 10$ min, 20 min, 30 min, ..., 3 hours. The cross-correlation
81 coefficient $C_{G_1 G_2}$ is used for each time scale T . From this result, we determine the time scale
82 threshold T_{trs} : for $T < T_{trs}$, the two signals are decorrelated and for $T > T_{trs}$, the two signals are
83 correlated. To evaluate the scattering effect of two sites, we determine the coefficient of variation
84 for the sum signal G_{1+2} .

85 Finally we propose, analytical relationship of coefficient of variation I_{1+2} for two cases i) two signals
86 statistically independent with different momentum, ii) two signals correlated with different
87 momentum.

88 **2.Theoretical frame**

89 **2.1 Decomposition of solar radiation signal using moving average filter**

90 The moving average of the instantaneous solar radiation G , at a given instant t for a given averaging
91 time T , is defined as(Papoulis):

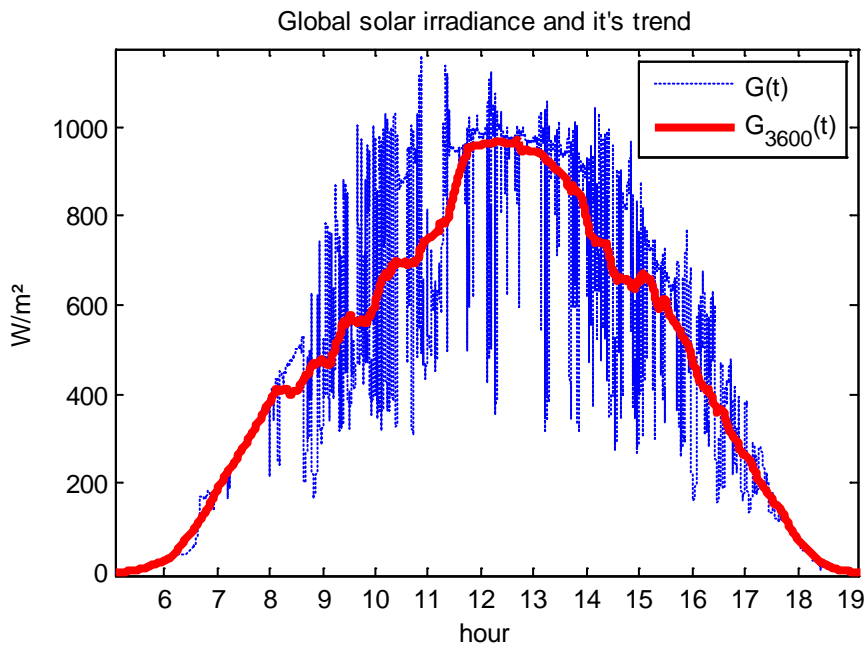
$$92 \quad \overline{G}_T(t) = \frac{1}{N} \sum_{i=t-\frac{T-1}{2}}^{i=t+\frac{T+1}{2}} G(i) \quad (1)$$

93 The instantaneous solar radiation G can then be expressed as (ref):

94
$$G(t) = \overline{G_T}(t) + G'_T(t) \quad (2)$$

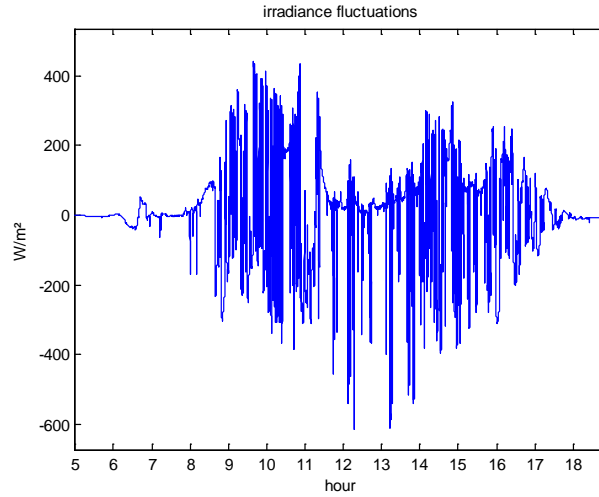
95 Where $G'_T(t)$ is the solar radiation fluctuation for time scales smaller than T while the moving
96 average $\overline{G_T}(t)$ gives the solar radiation evolution for time scales larger than T . This decomposition
97 is illustrated in figure (1), where $\overline{G_T}(t)$ is superimposed to $G(t)$ for a measurement duration of one
98 day and for $T = 3600s$. Figure (1.a) illustrates the fluctuations obtained from equation (2).

99



100

101 Figure1: An example of instantaneous solar radiation signal (red line) and it's trend (black line).



102

103 Figure 1a: global solar radiation fluctuations obtained from moving average decomposition

104

105 Besides, the difference between two moving average having respectively averaging time T_1 and T_2 ,
 106 gives the fluctuation for time scales ranging on $[T_1, T_2]$:

107
$$G'_{T_1-T_2}(t) = \overline{G_{T_1}}(t) - \overline{G_{T_2}}(t) \quad (3)$$

108

109 **2.2 Coefficient of variation defined for two sites.**

110 In this study we consider solar radiation signal of 10 min length defined arbitrary. Let consider $G_1 \left\{ \begin{matrix} \overline{G}_1 \\ \sigma_1 \end{matrix} \right.$
 111 and $G_2 \left\{ \begin{matrix} \overline{G}_2 \\ \sigma_2 \end{matrix} \right.$ two signals measured at site 1 and 2 respectively. We can define, for each G_1 and G_2 ,
 112 from the two momentums \overline{G} and σ , the coefficient of variation, a normalized measurement of
 113 dispersion of a probability distribution as:

114
$$I = \frac{\sigma}{\overline{G}}$$

115

116 This parameter is a second order statistic moment measuring the degree of variability of a given
 117 process. In the turbulence and the wind energy communities, it's called turbulence intensity and is
 118 classically used. Turbulence intensity is a metric characterizing turbulence expressed as a percent.
 119 For an illustration, an idealized flow of air with absolutely no fluctuations in air speed would have
 120 a turbulence intensity value of 0%. This idealized cases never occurs on earth. However, the values
 121 greater than 100% are possible. This can happen, for example, when the average air speed is small
 122 and there are large fluctuations present. The higher the coefficient is, the more turbulent the flow.
 123 This parameter is computed for the first time with global solar radiation data. This could be an
 124 interest for the solar energy community. It could be a simple way in order to qualify and classify the
 125 variability level of sites.

126

127 Let consider the sum G_{1+2} is defined by $G_{1+2} \begin{cases} \bar{G}_{1+2} \\ \sigma_{1+2} \end{cases}$ with $G_{1+2} = G_1 + G_2$ and $\bar{G}_{1+2} = \bar{G}_1 + \bar{G}_2$

128 Let us define σ_{1+2} . By definition of standard deviation

129
$$\sigma_G = \sqrt{(G - \bar{G})^2}$$

130 thus,

131
$$\sigma_{1+2} = \sqrt{(G_1 + G_2)^2 + (\bar{G}_1 + \bar{G}_2)^2 - 2(G_1 + G_2)(\bar{G}_1 + \bar{G}_2)}$$

132 This equation becomes

133
$$\sigma_{1+2} = \sqrt{G_1^2 + G_2^2 + 2\bar{G}_1\bar{G}_2 + \bar{G}_1^2 + \bar{G}_2^2 + 2\bar{G}_1\bar{G}_1 - 2\bar{G}_1\bar{G}_2 - 2\bar{G}_2\bar{G}_1 - 2\bar{G}_2\bar{G}_2}$$

134 A) Assuming that G_1 and G_2 are statistically independent and have same moment order:

135 We have

$$136 \quad \overline{G_1 G_2} = \overline{G_1} \overline{G_2}$$

137 And

$$138 \quad \overline{G_1} = \overline{G_2}$$

139 With this assumption equation (2) becomes:

$$140 \quad \sigma_{1+2} = \sqrt{2(\overline{G_1^2} - \overline{G_1}^2)}$$

141 Hence we can define the coefficient of variation of G_{1+2} as:

$$142 \quad I_{1+2} = \frac{\sigma_{1+2}}{\overline{G_{1+2}}} = \frac{\sqrt{2(\overline{G_1^2} - \overline{G_1}^2)}}{2\overline{G_1}}$$

$$143 \quad I_{1+2} = \frac{1}{\sqrt{2}} \frac{\sigma_1}{\overline{G_1}} \quad (4)$$

144 This result can be extended to n independent signals having the same moments:

$$145 \quad I_n = \frac{\sqrt{(\sum_{i=1}^n \sigma_i^2)}}{\sum_{i=1}^n \overline{G_i}} \quad (5)$$

146

147 *B) Let us now consider G_1 and G_2 two signals statistically independent with different*
148 *momentum.*

149 We can decompose each signal as $G = \overline{G} + G'$

150 Where G' is the fluctuation in the signal around the mean value \overline{G} .

151 Thus the sum is

152 $G_{1+2} = \overline{G_1} + G_1' + \overline{G_2} + G_2'$

153 $G_{1+2} = \overline{G_1} + \overline{G_2} + G_1' + G_2'$

154 $G_{1+2} = \overline{G_{1+2}} + G_{1+2}'$

155 With

156 $\overline{G_{1+2}} = \overline{G_1} + \overline{G_2}$

157 and $G_{1+2}' = G_1' + G_2'$

158 The standard deviation of G_{1+2} is

159
$$\sigma_{1+2} = \sqrt{(G_{1+2} - \overline{G_{1+2}})^2}$$

160 Elsewhere $\sigma_{1+2} = \sqrt{(G_1' + G_2')^2} = \sqrt{(G_1'^2 + 2G_1'G_2' + G_2'^2)}$

161

162 As the signals are considered statistically independent and decorrelated, we have

163
$$\text{Corr}(G_1', G_2') = c = \frac{\overline{G_1'G_2'}}{\sigma_1\sigma_2} = 0$$

164 Where c is the normalized correlation coefficient

165 Thus $\overline{G_1'G_2'} = 0$

166 And

167
$$\sigma_{1+2} = \sqrt{(G_1'^2 + G_2'^2)} = \sqrt{(\sigma_1^2 + \sigma_2^2)}$$

168 And the variation coefficient is

169
$$I_{1+2} = \frac{\sqrt{\sigma_1^2 + \sigma_2^2}}{\overline{G_1 + G_2}} \quad (6)$$

170 *C) Now let us consider two signals correlated with different momentum as*

171
$$c = \frac{\sqrt{G_1' G_2'}}{\sigma_1 \sigma_2} \text{ and } \sigma_{1+2} = \sqrt{(G_1'^2 + 2G_1' G_2' + G_2'^2)}$$

172
$$\sigma_{1+2} = \sqrt{\sigma_1^2 + 2(c \sigma_1 \sigma_2)^2 + \sigma_2^2}$$

173 As said previously c is the normalized correlation coefficient and the variation coefficient is

174
$$I_{1+2} = \frac{\sqrt{\sigma_1^2 + 2(c \sigma_1 \sigma_2)^2 + \sigma_2^2}}{\overline{G_1 + G_2}} \quad (7)$$

175 Consequently, using the analytical relation given above, considering two signals
 176 decorrelated, $c=0$, we found the analytical expression given in equation 6. Besides, if we
 177 consider two signals correlated, $c=1$, the analytical relation given 7 becomes:

178
$$I_{1+2} = \frac{\sqrt{\sigma_1^2 + 2(\sigma_1 \sigma_2)^2 + \sigma_2^2}}{\overline{G_1 + G_2}}$$

179 **3 Solar radiation measurements**

180 In this study, the solar radiation measurements sampled at 1hz were measured during one
 181 year, from January 2006 to January 2007, at two different sites in Guadeloupe. The daily average
 182 for the solar load on a horizontal surface is around 5 kWh/m². A constant sunshine combined with
 183 the thermal inertia of the ocean makes the air temperature variation quite weak, between 17°C and
 184 33°C with an average of 25°C to 26°C. Relative humidity ranges from 70% to 80% and the trade
 185 winds are relatively constant all along the year. Two main regimes of cloudiness are superposed:

186 the clouds driven by the synoptic conditions over the Atlantic Ocean and the orographic cloud layer
 187 generated by the local reliefs.

188 4 Results

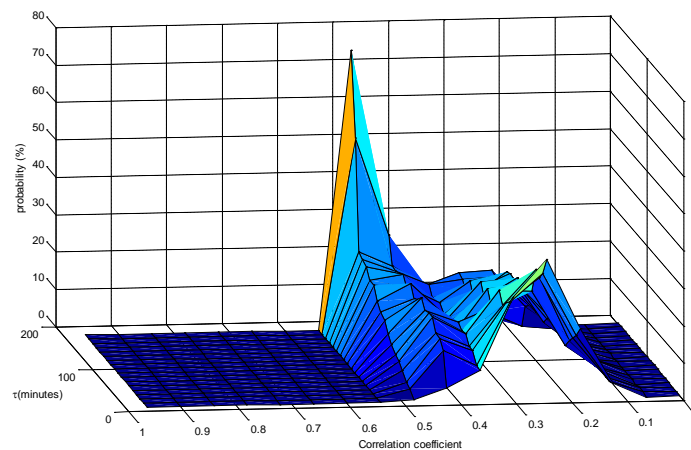
189 4.1 Time scale separation

190 To put in evidence an eventually dynamical correlation between the two sites, the cross-
 191 correlation coefficient $C_{G'_1 G'_2}$ is defined as [3]:

$$192 \quad R_{G'_1 G'_2}(\tau) = \begin{cases} \sum_{n=0}^{T-\tau-1} G'_{1n+\tau} G'_{2n} & \tau \geq 0, \\ R_{G'_1 G'_2}(-\tau) & \tau < 0 \end{cases}$$

$$193 \quad C_{G'_1 G'_2}(\tau) = \frac{R_{G'_1 G'_2}(\tau)}{\sigma_{G'_1} \sigma_{G'_2}}$$

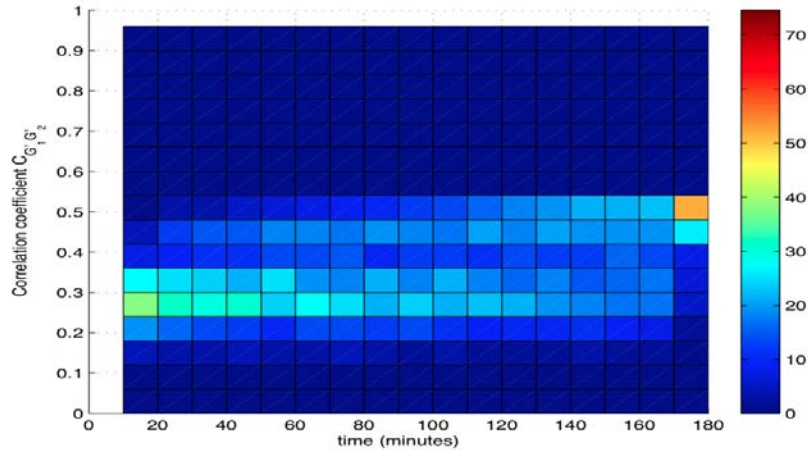
194 Where G'_1, G'_2 are zero-mean stochastic variables, $\sigma_{G'_1}$ and $\sigma_{G'_2}$ are the corresponding
 195 standard deviation . For each day we have calculated this coefficient $C_{G'_1 G'_2}$ for different
 196 time scales.



197

198

Figure 2: The conditional probability of the cross correlation.



199

200

Figure 3: percentage of correlation values for different τ

201

For the highlighting of a threshold time T_{trs} under which the fluctuations of two sites

202

are not correlated, we determine the correlation coefficient $C_{G'_1, G'_2}(\tau)$ for the fluctuations

203

$G'_{T_1-T_2}(t)$ defined in equation 3, with $T_1=10j$ minutes and $T_2=T_1+10$ minutes, for j between

204

1 and 18. The figure illustrates the conditional probability $P(C_{xy}|\Delta t)$, with $\Delta t = T_2 - T_1$. We

205

observe that the maximum value of the probability increase 0.25 to 0.5 for time range

206

[10;170] minutes. We observe a significant correlation for time [160; 170] and $C_{G'_1, G'_2} = 0,5$.

207

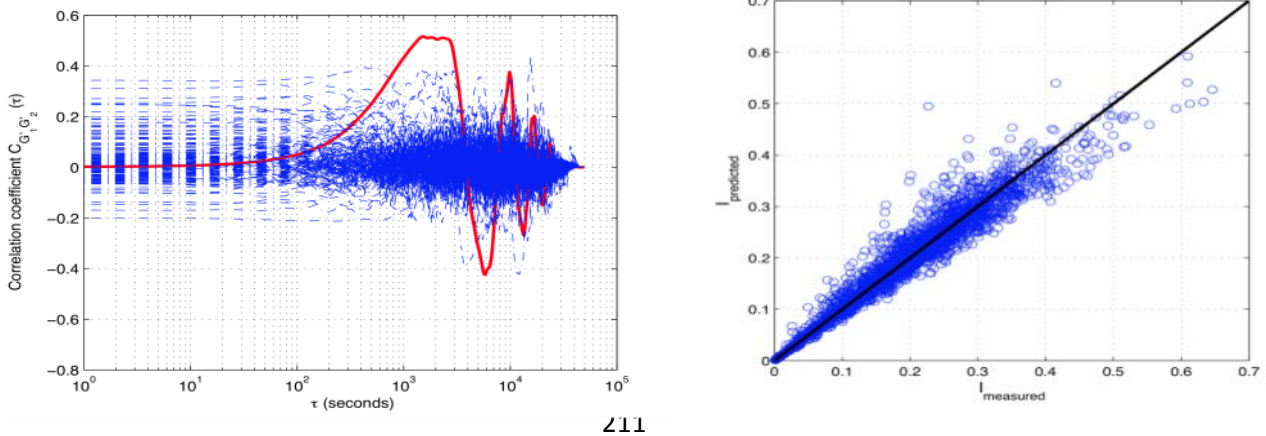
This correlation keeps increasing for higher time scale. Thus the threshold time is estimated

208

to be $T_{trs} = 170 \text{ min}$.

209

210 **4.2 Time scales for uncorrelated signals: $T < T_{trs}$.**

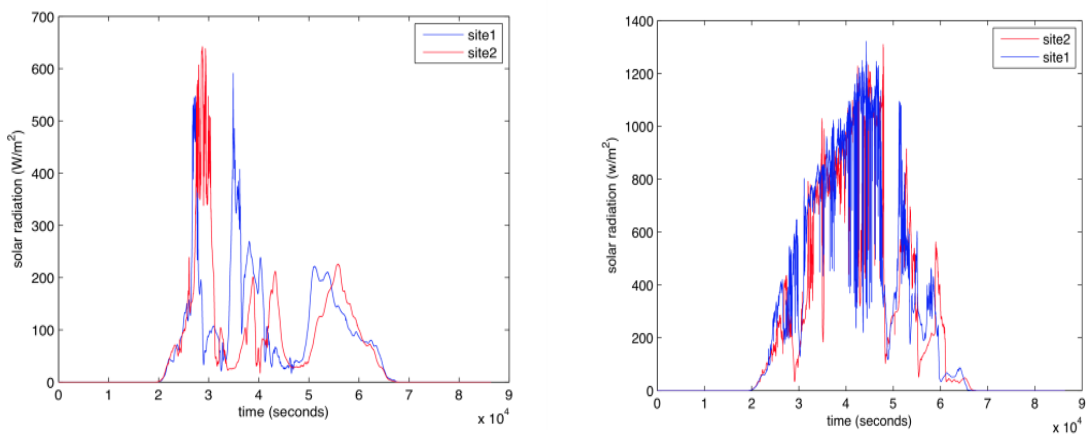


211

212 Figure 4: a (left) The cross correlation function in semi-log diagram. The red curve correspond to the cross
 213 correlation for an example of a marginal event, and the blue curve represent the cross correlation for the
 214 majority of the events. b(right) the predicted coefficient of variation versus the experimental coefficient of
 215 variation.

216 In this section, the figure 3a presents the cross correlation coefficient of the two
 217 sites, for time scales $T < T_{trs}$. In 97% of cases, the value of $C_{G_1 G_2}(\tau)$ is smaller than 0,4. For
 218 time going to [10; 50] minutes the maximum correlation coefficient is $C_{G_1 G_2} = 0,25$.

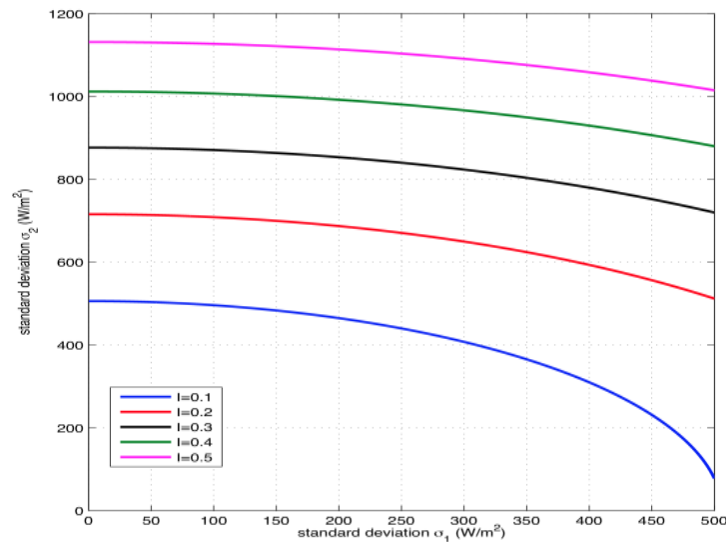
219 A weak value of the cross correlation coefficient for two measurement sites
 220 indicates that the solar radiation fluctuations are statistically independent. This shows
 221 that the fluctuations are not correlated on these time scales.



222 Figure 5: Examples of correlated marginal events for small time scales.

223 However, in 2% of cases we observe a dynamical correlation for C_{xy} values superior to 0,5.
 224 These marginal events correspond to extreme meteorological situations (clear sky or cloudy
 225 sky) as illustrated in figure 4.

226 Besides, for these time scales, in figure 3b, we have plotted the experimental coefficient
 227 variation $I_{1+2exp} = \frac{\sigma_{1+2}}{G_{1+2}}$ versus the analytical relationship given in equation 6, $I_{1+2theo} =$
 228 $\frac{\sqrt{\sigma_1^2 + \sigma_2^2}}{G_1 + G_2}$. A good agreement is observed between the predicted coefficient variation and the
 229 measured coefficient variation, confirming a non-synchronous variability of the two sites
 230 for times scales $T < T_{Trs}$.



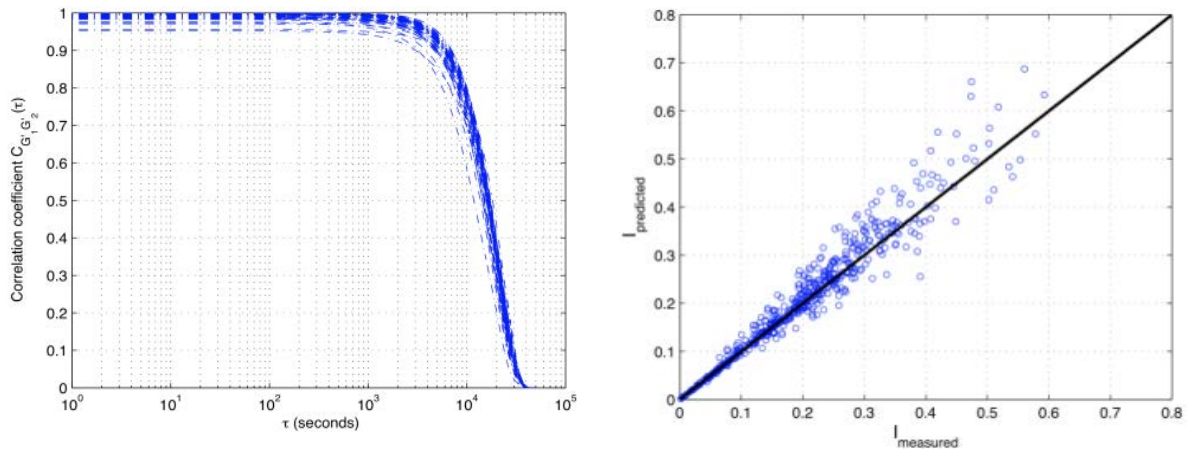
231

232 Figure 6: Diagram of the predicted coefficient of variation determined with the standard deviations of two
 233 sites, uncorrelated cases.

234 Moreover, in figure 6, we give the evolution of the predicted coefficient variation versus
 235 the given standard deviation σ_1 and σ_2 , respectively for a site 1 and site 2.

236

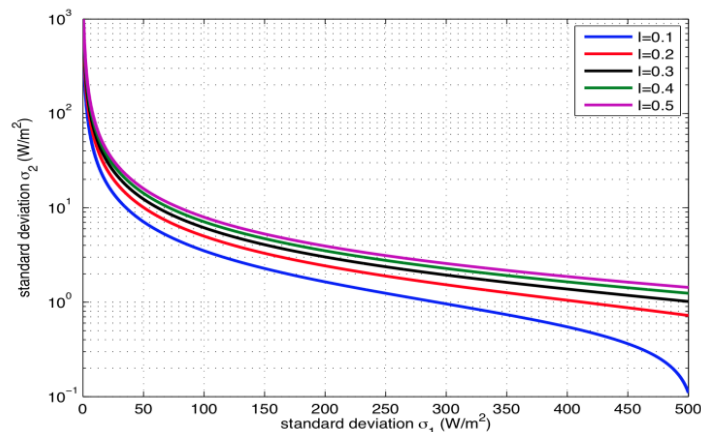
237 **4.3 Time scales for correlated signals: $T > T_{trs}$**



238 Figure 7: a (left) the cross correlation coefficient in semi-log diagram. b(right) the predicted coefficient of
 239 variation versus the experimental coefficient of variation.

240 The figure 7a displays the cross correlation of the two sites, for time scales $T > T_{trs}$. We can
 241 observe that the cross correlation coefficients almost are close to 1 obtained for a time
 242 delay equal to 0.

243 For these time scales, the characteristic length of the convective structure, in the
 244 atmospheric sub- layer, is of the order of several hundreds of kilometers (ref); we recall that
 245 the distance between the two sites is around to 40 kilometers.



246
 247 Figure 8: Diagram of the predicted coefficient of variation determined with the standard deviations of two
 248 sites, correlated cases.

249 For these time scales, we illustrated in figure 7b, the predicted coefficient of variation
250 $I_{1+2\text{theo}}$ given in equation 7, is plotted versus the experimental coefficient of variation,
251 indicating a good agreement between the predicted values and the measured values. The
252 figure 8 presents the evolution of the predicted coefficient of variation versus the given
253 standard deviation σ_1 and σ_2 , respectively for a site 1 and site 2.

254 **5. Discussions**

255 In this study, we attempt to quantify the variability and the coupling of the global solar
256 radiation for two sites in Guadeloupe, through the coefficient of variation, on ten minutes
257 interval. This coefficient is defined from the mean and standard deviation of solar irradiance
258 over the considered interval.

259 We have established a model for the coefficient of variation assuming a time scale
260 separation. Two cases can be distinguished according to the correlation of the first order
261 moment (mean).

262 The analysis of the cross correlation coefficient put in evidence à threshold under which
263 there is no significant correlations of the global solar radiation fluctuations. According to
264 this assumption we have established a model for the coefficient of variation defined for a
265 pair of site, each one being characterized by the first and second order momentums \bar{G} and
266 σ . This is given by the equation (6).

267 When the signal are significantly correlated, the coefficient of variation of a pair of site is
268 given by equation (7).

269 Hence according to this model we can determine the coefficient of variation of a pair of site
270 knowing the mean and standard deviation on one of the sites.

271 The model was tested on experimental data for both cases, correlated and non-correlated.
272 In both cases the predicted values by the model are in good agreement with the calculated
273 coefficient of variation.

274 For both cases a diagram is proposed to determine the coefficient of variation of a pair of
275 site. This model can be useful to determine in a very simple and easy way the amount of
276 energy and the associated fluctuations that may occur on a pair of site knowing the
277 conditions on one site.

278 When considering the PV production on different sites, it becomes possible to estimate the
279 smoothing effect of the sum knowing the PV power at one site.

280 This study cans also be helpful in choosing the best places for PV plants to take advantage
281 of the smoothing effect due to the connection of different sites.

282

283 **References**

284 [1] G. Notton, C. Cristofari, P. Poggi, M. Muselli, Calculation of solar irradiance profiles from
285 hourly data to simulate energy systems behaviour. *Renewable Energy* 27 123–142, 2002.

286 [2] G. Notton, M. Muselli and A. Louche, Two estimation methods for monthly mean hourly
287 total irradiation on tilted surfaces from monthly mean dayly horizontal irradiation from
288 solar radiation data of Ajaccio. *Solar Energy* Vol. 57, No. 2, pp. 141-153. 1996

289 [3] S. Papoulis et S. Unnikrishna Pillai. *Probability, Random variables and stochastic*
290 *processes*. Mc Graw Hill, 2002.

- 291 [4] R. Perez, J. Schlemmer, S.Kivalov, K. Hemker Jr, T. Hoff, Short term irradiance station
292 pair correlation as a function of distance, American Solar Energy Society, ASES Conference,
293 Raleigh, 2011.
- 294 [5] R. Perez, S. Kivalov, J. Schlemmer, K. Hemker, T.Hoff, Parameterization of site-specific
295 short-term irradiance variability, Solar Energy Volume 86, Issue 8, August 2012, Pages
296 2170–2176.
- 297 [6] M. Lave, J. Kleissl, Solar variability of four sites across the state of Colorado, Renewable
298 Energy 35 (2010), Pages 2867-2873.
- 299 [8] C. Monteiro, L. Fernandez-Jimenez, I. Ramirez-Rosado, A. Munoz-Jimenez, and P. Lara-
300 Santillan, "Short-term forecasting models for photovoltaic plants: Analytical versus soft-
301 computing techniques," Mathematical Problems in Engineering, vol. 2013, 2013.
- 302 [9] M. Bouzerdoum, A. Mellit, and A. Massi-Pavan, "A hybrid model (sarima–svm) for short-
303 term power forecasting of a small-scale grid-connected photovoltaic plant," Solar Energy,
304 vol. 98, pp. 226–235, 2013.
- 305 [10] Marquez R, Coimbra CFM. Proposed Metric for Evaluation of Solar Forecasting
306 Models. J Sol Energy Eng 2012;135:011016–011016. doi:10.1115/1.4007496.
- 307 [11] P.Mandal, S. Madhira, J.Meng, and R. Pineda, "Forecasting power output of solar pho-
308 tovoltaic system using wavelet transform and artificial intelligence techniques," Procedia
309 Computer Science, vol. 12, pp. 332–337, 2012.
- 310 [12] E. Lorenz, J. Hurka, D. Heinemann, and H. Beyer, "Irradiance forecasting for the power
311 prediction of grid-connected photovoltaic systems," IEEE Journal of Selected Topics in
312 Applied Earth Observations and Remote Sensing, vol. 2, no. 1, pp. 2–10, 2009.

313 [12] J. Shi, W. Lee, Y. Liu, Y. Yang, and P. Wang, "Forecasting power output of photovoltaic
314 systems based on weather classification and support vector machines," *Industry Applica-*
315 *tions, IEEE Transactions on*, vol. 48, no. 3, pp. 1064–1069, 2012.

316

317

318