A SIMPLE CLOUD SIMULATOR FOR INVESTIGATING THE CORRELATION SCALING COEFFICIENT USED IN THE WAVELET VARIABILITY MODEL (WVM)

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ABSTRACT

A wavelet variability model (WVM) for simulating solar photovoltaic (PV) powerplant output given a single irradiance sensor as input has been developed and has tested well against powerplants in Ota City, Japan and Copper Mountain, Nevada [1-3]. Central to this method is a correlation scaling coefficient (A) that calibrates the decay of correlation as a function of distance and timescale, and varies by day and geographic location. For Ota City and Copper Mountain, this A value has been determined using the network of irradiance sensors located at each powerplant. However, for applying the WVM to arbitrary locations where an irradiance sensor network is not readily available, it is necessary to estimate the A value. In this paper, we examine the dependence of A values on wind speed (at cloud altitude) and cloud size using a simple cloud motion simulator.

1. INTRODUCTION

The variability of solar irradiance can be an obstacle to installing large PV powerplants: grid operators may be concerned about the amount of variability a new PV powerplant will introduce into the grid. To help predict the variability of potential PV powerplants, we have developed a wavelet-based variability model (WVM) that simulates the variability in PV powerplant output given limited inputs[1, 2]. The WVM scales up, taking the timeseries of a single irradiance point sensor as input, then using a wavelet transform and estimating the variability reduction due to geographic smoothing over the entire plant to simulate the power output of the entire PV powerplant. In this way, the WVM can be used to estimate the variability of a yet-to-be built solar PV plant, or the relative variability reduction benefit of adding more PV to an existing plant.

In order to simulate geographic smoothing, the WVM models the correlations, ρ, between pairs of sites (i.e., between pairs of PV modules in a powerplant) as a function of distance, $d_{m,n}$, and timescale, $\bar{t}$:

$$\rho\left(d_{m,n}, \bar{t}\right) = \exp\left(-\frac{1}{A}\frac{d_{m,n}}{\bar{t}}\right). \tag{1}$$

A is the correlation scaling coefficient, which varies by day and by site. Currently, the A value has been found empirically from a network of irradiance sensors at the site of interest, limiting the potential locations for application of the WVM. While most current PV powerplants do have dense irradiance sensor networks, there are very few other locations with a dense enough network of high-temporal resolution sensors to allow for determination of A values. In this paper, we create synthetic cloud fields, giving a test "laboratory" where we can change the wind speed and typical cloud size to determine the effect of these physical variables on A values. The goal is to obtain a better understanding of the behavior of A values, which should facilitate their prediction in areas without sensor networks.

2. BACKGROUND

The key factors to the variability of PV powerplant output are the footprint and density (e.g., central or distributed) of PV at the plant. While solar power from one module may be highly variable, the relative variability will be reduced when the many modules are aggregated into the entire plant. While adding more modules reduces the relative variability, the amount of this reduction depends on the geographic diversity of the plant and the spatial decorrelation scale of cloud cover. Both of these affect the correlation between PV modules: the lower the correlation, the more diverse the modules' output and the more heterogeneous the cloud field, leading to more geographic smoothing. Several previous studies have quantified the correlation between sites, and used this as a metric to simulate power plant variability.

Step changes (deltas) in block averages of the clear-sky index for 23 Southern Great Plains (SGP) GHI stations, with sites separated by 20 to 440km showed that 1- and 5-min fluctuations had nearly zero correlation between all sites, even at 20km distances, but deltas for times longer than 5-min increased in correlation with decreasing distance [4]. Through simulation, the authors determine that six times less reserve resources are required to mitigate fluctuations for a distributed plant over 20 x 20 km than would be required for a central plant of the same power capacity.

Another study used 24 irradiance sensors – 17 stations in the ARM network and 7 stations in the SURFRAD network – to create virtual networks of irradiance sensors by displacing and time-shifting the sensor measurements [5]. 20-sec, 1-min, 5-min, and 15-min fluctuations become uncorrelated at 500m, 1km, 4km, and 10km, respectively. The authors extrapolate the correlation relationships to model a homogeneously dispersed solar resource over a 40x40 km grid, and find variability to be reduced by a factor of 80, 40 10, or 4 over the variability of a single site. Further work [6] has shown that the correlation values collapse onto a line when the distance is divided by timescale. Accounting for cloud speed as determined from satellite further decreased the scatter suggesting a universal correlation law based on distance, timescale, and cloud speed.

With a similar objective to the WVM, [7] used a solar irradiance point sensor timeseries to simulate variability of a larger power plant. A cut-off frequency was defined as the intersection of short-timescale and long-timescale linear fits of the irradiance Fourier power spectrum. A smaller cut-off frequency indicated smoothing up to a longer timescale, and cut-off frequency was found to exponentially decay with increasing PV plant area. To simulate a power plant form a single irradiance sensor, a transfer function based on a low pass filter which is scaled by the power plant area is used. Validation against actual PV power output showed good agreement between maximum power fluctuations of simulated and actual data.

3. WVM PROCEDURE

In this section, we give a brief outline of the WVM. A full description of the WVM process is given in [2]. The WVM simulates power plant output given measurements from only a single irradiance point sensor by determining the geographic smoothing that will occur over the entire plant. The simulated powerplant may be made up of either distributed generation (i.e., a neighborhood with rooftop PV), centrally located PV as in a utility-scale powerplant, or a combination of both. In the WVM, we assume a statistically invariant irradiance field both spatially and in time over the day, and we assume that correlations between sites are isotropic: they depend only on distance, not direction. The main steps to this procedure are:

1) Apply a wavelet transform to the clear-sky index of the original point sensor irradiance timeseries, decomposing the clear-sky index into wavelet modes $w_{\bar{t}}(t)$ at various timescales, $\bar{t}$, which represent cloud-caused fluctuations at each timescale.
2) Determine the distances, $d_{m,n}$, between all pairs of sites in the PV powerplant; $m = 1, \ldots, N, n = 1, \ldots, N$.
3) Determine the correlations, between the irradiances at all sites in the plant at timescales corresponding to wavelet modes using the equation: $\rho\left(d_{m,n}, \bar{t}\right) = \exp\left(-\frac{1}{A}\frac{d_{m,n}}{\bar{t}}\right)$. If unknown, the A value will first have to be determined. One way to determine the A value is to use a network of sensors to calculate the correlations between sensor pairs. An example of this is shown in Fig. 1.

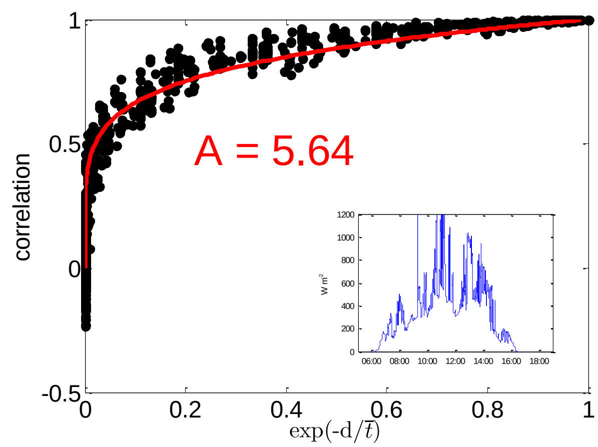

Fig. 1: Sample relationship between correlation and the quantity $exp(-d/\bar{t})$. In this case, $A = 5.64$.

4) Use the correlations to find the variability reduction, VR($\bar{t}$), at each timescale.
5) Scale each mode of the wavelet transform by the VR corresponding to that timescale to create simulated wavelet modes of the entire power plant. Apply an inverse wavelet transform to create a simulated clear sky index of areal-averaged irradiance over the whole powerplant, $< GHI_{norm}^{sim} >_{pp} (t)$.
6) Convert this area-averaged irradiance into power output, $P(t)^{sim}$ using a clear-sky power model. Clear-sky power models range from simple linear models to more complicated, temperature dependent, non-linear models.

Here, we focus on step (3): the determination of correlations by studying how the A value changes with changing sky conditions.

a) b)

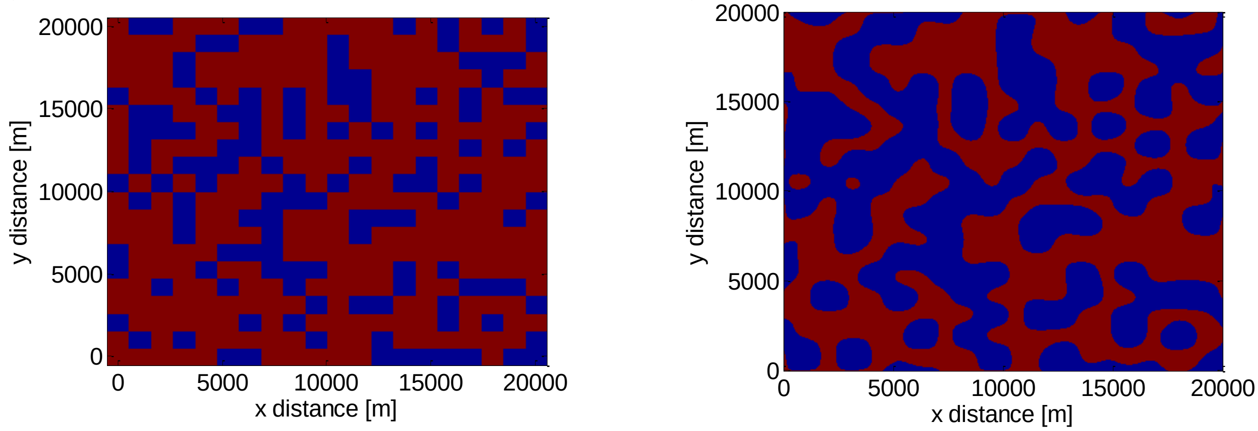

Fig. 2: (a) Coarse cloud field and (b) fine cloud field. Red represents clouds and blue represent clear-sky. These images were created for the case where the typical cloud size was 1000m, and the cloud cover threshold was 0.7.

4. <u>Cloud Simulation Methods</u>

For study of *A* values, we created a cloud simulator that creates a cloud field with a specified typical cloud size, and advects this cloud field at a specified wind speed. Here, we opted for a very simple model, partially based on previous experience which has shown more complicated cloud field simulation methods to be very computationally expensive. The cloud field simulation method we used can be described in these steps:

1) Picked a fine grid size over which to simulate. For this work, we used grids between 10,000 by 10,000 and 20,000 by 20,000 pixels (the smaller grid sizes were used as computation limits required).
2) Created a coarse grid where one pixel represented an area the size of the specified typical cloud size. For example, if the typical cloud size was 1000m and the fine grid was 20,000 by 20,000, the coarse grid would be 20 by 20 pixels.
3) Placed a uniformly distributed ([0 1]) random number at each of the pixels on the coarse grid. Picked a cloud cover fraction: in this work, cloud cover of 0.7 (70% of sky covered by clouds) was always used. Set all randomly generated pixel values that were less than the specified clear-sky threshold to one to represent clouds, and all greater than the threshold to zero to represent clear-sky. In this way, a coarse cloud field is created, examples of which are shown in Fig. 2a and Fig. 3a.
4) The coarse cloud field was converted to a fine cloud field using a 2D spline interpolation. After the interpolation, values that were greater than 0.8 were retained as clouds (set to a value 1), and values less than 0.8 were set to clear-sky. If there were only one cloud pixel surrounded by clear-sky, using a value of 0.8 (instead of 0.5) would have the effect of slightly reducing the cloud size. However, in this case, there are many examples of clouds merging together, and we found the value of 0.8 to return the best results. Example fine cloud fields are in Fig. 2b and Fig. 3b.

a) b)

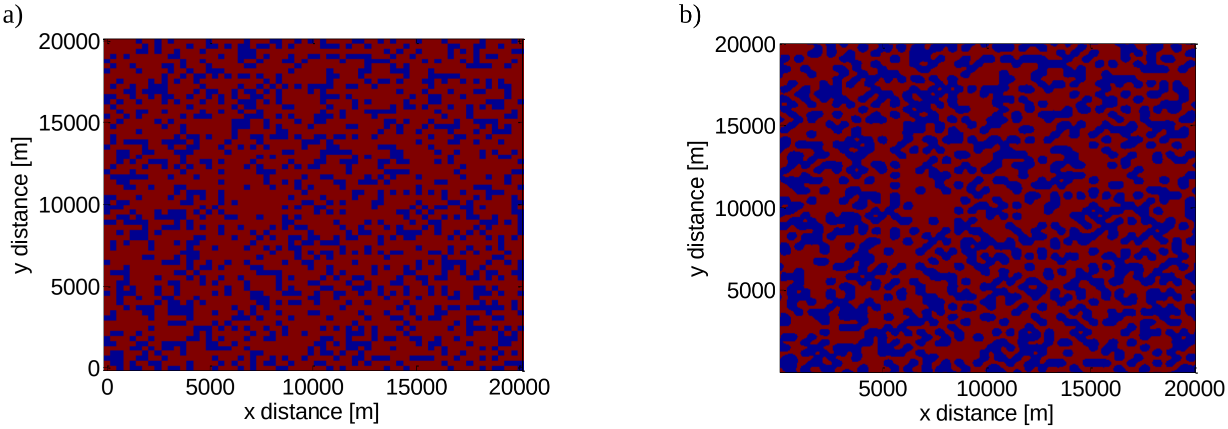

Fig. 3: Same as Fig. 2but for a typical cloud size of 300m.

5) Picked sensor locations to focus on. We chose 9 points in the bottom right of the cloud field spaced in a 100m by 100m grid. Then, the cloud field was advected to the right based on the wind speed. This resulted in a timeseries sampled once per second. The length of the timeseries depended on the grid size and the cloud speed: for 1 m/s wind speeds, timeseries 10,000 seconds long were created, while for 25 m/s wind speeds, the timeseries were only 800 seconds long.

Through steps (1-6), simulated irradiance timeseries were created. These simulated irradiance timeseries were used to calculate A values in the same way the ground sensors networks have been used to calculate A values in the past.

5. RESULTS

We ran the cloud simulation to determine A values for wind speeds at cloud height ranging from 1 m/s to 25 m/s, and for cloud sizes ranging from 100 m to 3000 m. Each combination of wind speed and cloud size was run 10 times, and the means of those 10 trials were recorded, and are shown in Fig. 4.

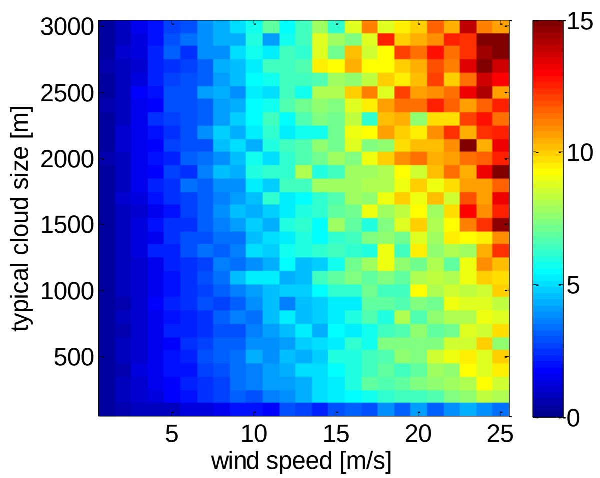

Fig. 4: A values calculated for each wind speed and cloud size.

The calculated A values show a clear trend of increasing from low to high wind speed, and also show a weaker trend of increasing from small to large cloud size. Since a larger A value indicates that sites are more highly correlated, this tells us that correlation between sites increases with increasing wind speed and with increasing cloud size. While the later is intuitive since with large clouds, it is more likely that the same cloud is covering both sites in a pair, the former requires some further thought. At higher cloud speeds, the amount of time it takes for the same cloud to travel between a pair of sensors in shorter, and so there will be a shorter lag time between the sensors. The shorter the lag time, the higher the correlations will be at each wavelet timescale that is longer than the lag time, since these correlations are centered on zero lag. In this simulation, we assume frozen cloud advection. This will not be true in the physical world, as cloud will be created, destroyed, and deform. However, the faster the wind speed the more similar the cloud field will be to frozen advection (since there will be less time to deform), and so correlations should still be higher for faster wind speeds.

To better understand the relationship between A values and wind speed and cloud size, we fit a function of the form:

$$A = C_1 ws + C_2 ws^2 + C_3(ws)(cs) + C_4 cs + C_5 cs^2, \quad (2)$$

where ws is the wind speed and cs is the cloud speed. The coefficients found for this function are shown in Table 1, and the function is plotted in Fig. 5.

Table 1: Coefficients corresponding to eq. (2).

Coefficient	Value
C_1	0.000455
C_2	0.270367
C_3	0.000103
C_4	0.000502
C_5	0.000000

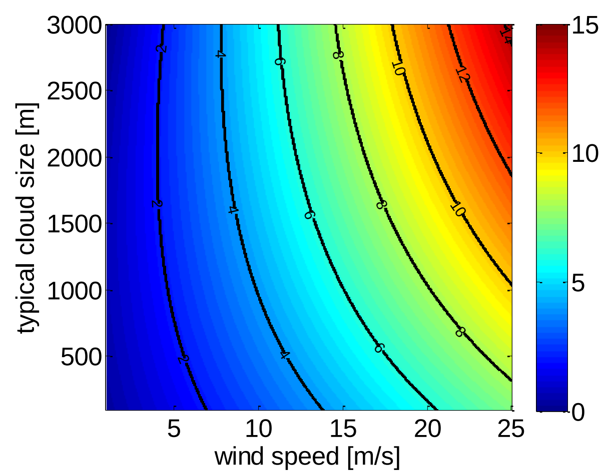

Fig. 5: A values modeled with the function in eq. (2) and the coefficients in Table 1.

Due to the very low values of all coefficients in Table 1 that multiply the cloud speed, and based on the fact that the units of A must be m/s to balance eq. (1), we now investigate modeling A values solely as a function of wind speed. Fig. 6

shows A values plotted against wind speed. A values show a clear linear increase with increasing wind speed, though there is some spread due to the varying cloud sizes. The line $A = 0.445 \times wind\ speed$ was found to fit the data best, and is shown in Fig. 6. This line has an R^2 value of 0.831, due to the spread in the data.

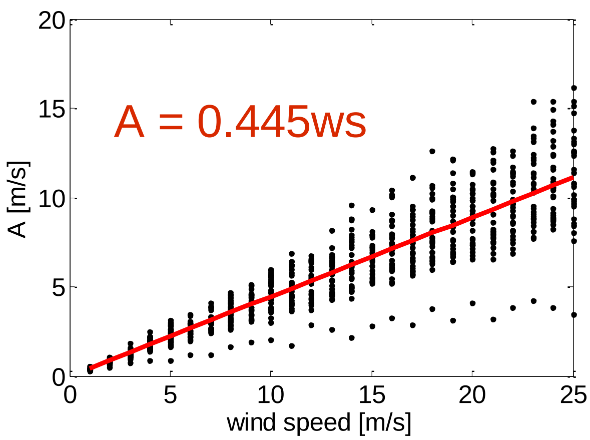

Fig. 6: A values plotted versus wind speed. The red line is the linear fit $A = 0.445 \times wind\ speed$. The lowest line of dots correspond to when cloud size was 100m, and are likely different due to issues with the cloud simulation at such a small cloud size.

6. Conclusion

The Wavelet Variability Model (WVM) has shown great promise in simulating the output of PV powerplants. At this point, though, in order to apply the WVM an irradiance sensor network is required to determine the correlation scaling coefficient (A). In this paper, we examined how A values change over various wind speeds (at cloud altitude) and cloud sizes by using a simple cloud simulator.

A values were found to increase both with increasing wind speed and with increasing cloud size. A function was created and plotted in Fig. 5 which can be used to compute the A value if the wind speed and cloud size are known. However, it was found that the impact of cloud size was small, and that A values were nearly linearly proportional to wind speed. This is an important finding because it simplifies the model for A to a linear equation, but more importantly, wind speeds (even at cloud altitude) are often much easier to measure than the much more arbitrary typical cloud size.

This paper has helped to gain a better understanding of A values and how they are related to physical variables. Future work will focus on testing the relationship between cloud height wind speed (possibly derived from sky imagery) and A values with measured data. If the nearly-linear relationship holds up, it may greatly simplify the determination of A values and allow for a much broader application of the WVM.

7. Acknowledgments

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8. References

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