Stochastic simulation of photovoltaic electricity feed-in considering spatial correlation

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Abstract: The growing generation capacity of electricity from renewable energy sources (RES-E) around the globe has an increasing impact on traditional energy and electricity markets. Well-ahead planned investment decisions as well as short term management of the power plant and storage dispatch and other challenges are highly dependent on the feed-in of RES-E. Therefore a thorough research of RES-E supply and knowledge about methods to generate corresponding model input is crucial when simulating electricity markets.

This work focuses on an approach to generate an arbitrary number of synthetic time series of weather data (solar radiation in this example) on a high spatial and temporal resolution in order to calculate electricity production from photovoltaic power plants. While each time series shall represent its location as realistic as possible, the dependencies between the different location's stochastic processes will be included The method to generate synthetic time series inheriting dependency is developed for the application in energy systems analysis. Key indicators of the calculated RES-E supply time series are emphasized and discussed in a quantitative way in an effort to contribute to the research of RES-E supply and their effects on distributed energy systems and grids.

1. Introduction

The stochastic characterization of solar irradiation and other weather parameters has been studied intensely in literature. The approaches can generally be divided into two categories: Firstly, Markov processes draw a random variable applying a transition matrix which represents the probabilities of future states in dependence of the past realizations. (e.g. [1] and [2]). Secondly, regression based models are based on drawing random variables applying an estimate of the probability distribution functions of the observations. Current and past realizations can be taken into account (e.g. [3] and [4]). Approaches of both methods are well advanced when simulating weather time series at single sites focusing on temporal correlation. They are well suited to generate irradiation profiles for energy systems analysis omitting limitations by a grid infrastructure. Current research considering multiarea simulation of RES-E supply as in [4] is yet limited to a small number of considered sites.

However, with the decentralization of energy systems through electricity generated from renewable energy sources and the rising importance of grid aspects, the consideration of spatial correlation becomes increasingly relevant. Ignoring the spatial dependency of RES-E supply may lead to a serious underestimation of their electricity generation. Therefore, in this work we explore an alternative methodology to generate any required volume of realistic photovoltaic feed-in data inheriting spatial dependency between different locations based on copula theory. This aims at enabling energy systems analysts to base their modelling approaches on a larger set of realistic data and thus reaching more robust and reliable results. In section 2 the principal stochastic simulation processes is described, followed by its application and illustrative results in section 3. It is finished with the main conclusions and indications of needs for further research in section 4.

2. A stochastic process to simulate solar radiation supply: model description

For our analysis we use extracts from historical irradiation data on a European scale with a temporal and spatial resolution of 10 minutes and 20x20km² provided by a numerical weather model. First, we adjust the time series of historical data in a linear way in order to remove deterministic effects which do not need a stochastic characterization for simulation. For this analysis we conducted the following two steps:

Subtraction of periodic and recurrent values: The irradiation from the sun can be forecasted in a perfectly deterministic way for a surface outside the earth's atmosphere The disturbances within the atmosphere result in a reduced level of irradiation to reach the earth's surface

Deploying 24 years of historical irradiation data on a 10 minute resolution, we construct a maximum irradiation curve which represents the maximum possible irradiation to reach the surface at a certain site and time step of the year. Through subtraction of this trend function we eliminate periodic elements of the time series and reduce the time series to information about the underlying stochastic in the atmosphere. Fig. 1 shows how the trend elimination explains large parts of the spatial correlation within the time series.

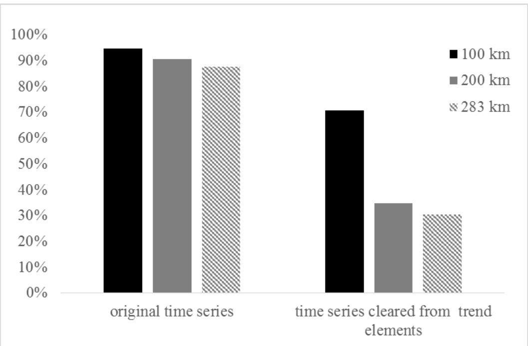

Fig. 1: *Spatial correlation before and after elimination of trend elements (as a function of spatial distance)*

Normalization of the time series: The second step of our adjustment generates a normalized times series with values limited to the range between [0,1] through division by the maximum irradiation curve introduced above. This helps to reduce the heteroscedasticity of the time series that occurs on a diurnal and seasonal (yearly) basis and thus enables us to implement a single irradiation process per site in contrast to modelling every time step of the day separately. The backwards-normalization also guarantees the simulated irradiation for every time step to be within a physically possible range. Both elements of time series adjustment can also reduce large parts for the autocorrelation within the data, especially for a lag of more than a few time steps (compare Fig. 2).

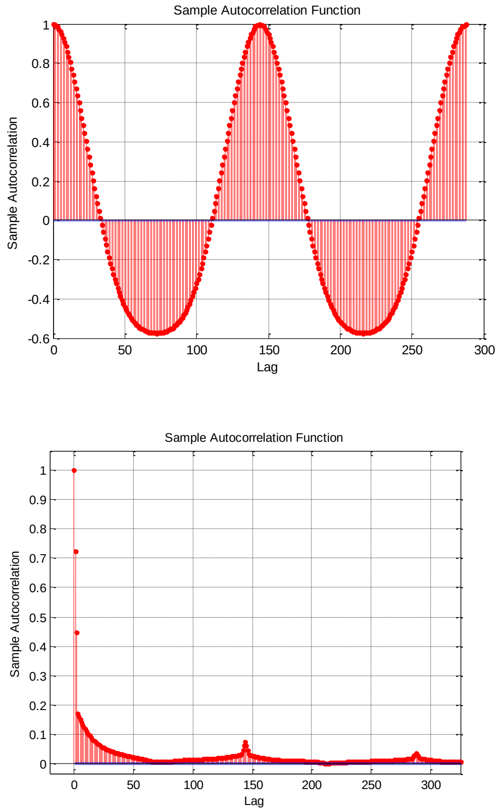

Fig. 2: *Autocorrelation with differing lags for the original time series (above) and the time series cleared from trend elements and after normalization (below)*

Based on work from [5] and [6], an approach is developed to simulate multiple time series representing simultaneous solar irradiation at various sites using copula theory. A copula can basically be described as a tool to draw from an arbitrary number of uniformly distributed random variables taking into account their dependency. Sklar's theorem postulates this idea to join together the one-dimensional cumulative distribution functions (cdf) F_X and F_Y of any random variables X and Y:

$$F_{XY}(x,y) = C(F_X(x), F_Y(y)) \qquad (1)$$

The copula C represents the method to transform any number of independent and one-dimensional random processes to a joint multivariate distributed random process. There exists a variety of different copula designs in literature. In this work, in order to join together the irradiation processes of numerous spatially distributed sites, we apply a Gaussian copula defined as follows:

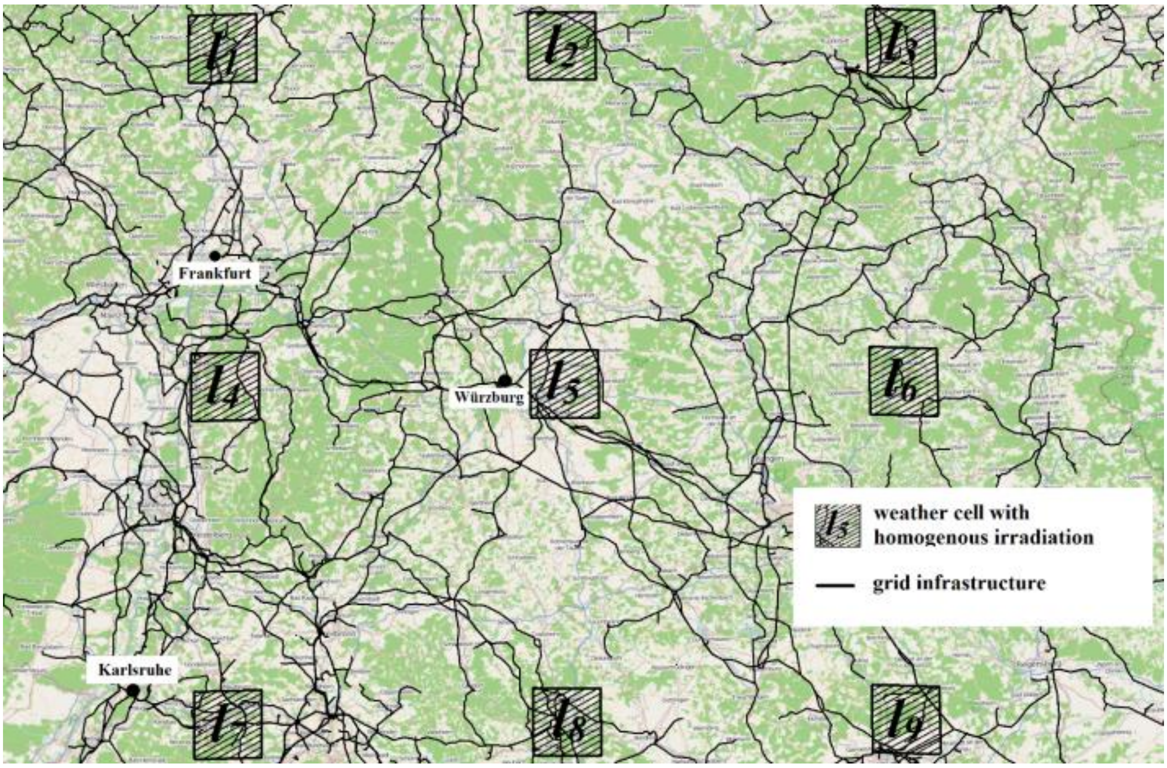

Fig. 3: Layout of the nine weather cells where the locations of the model PV-plants are assumed to be installd

$$C(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) = \Phi_n(\Phi^{-1}(\varepsilon_1), \Phi^{-1}(\varepsilon_2), \dots, \Phi^{-1}(\varepsilon_n)) \quad (2)$$

The random processes at each of the $n \in \mathbb{N}$ sites are represented by the independent random variables $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n$ that are uniformly distributed on the interval [0,1] and linked by the Gaussian copula C. Φ represents the standard normal distribution function and Φ_n the n-dimensional multivariate standard normal distribution function. In order to generate synthetic irradiation time series we apply the following steps:

1) Reduce deterministic parts and normalize the time series through the trend adjustment described above.
2) Estimate the matrix of linear correlation under a Gaussian copula from the historical time series.
3) Draw uniformly distributed random numbers for the n modelled sites applying the Gaussian copula.[1]
4) Back-transform the uniformly distributed time series to the original domain of solar irradiation using the inverse cdf.

[1] Step 2 and 3 were performed using the functions copulafit and copularnd from MathWorks Matlab software.

The transformation between the uniform distribution and the empirical distribution is done by standard inverse transformation methods which can be applied to draw random numbers following any desired empirical distribution: May X be a random variable and F_X its invertible cdf with:

$$F_X(x) = P(X \leq x) \quad (3)$$

Then $F_X(X)$ is uniformly distributed: $F_X(X) = U \in [0,1]$ and the inverse empirical cdf $F_X^{-1}(U)$ follows the distribution of X. [5]

3. Application and results with regard to the influence of spatial correlation of different locations on the PV power supply

For modelling the solar power generation, we apply the PV model of [2] which includes an implementation of the physical model of [7]: The (horizontal) global irradiation is transformed into electrical power in dependency of the ambient temperature and technical properties of the PV system (e.g. orientation, module efficiency, etc.). In order to illustrate the effect of spatial correlation on the PV power supply, we generate time series for an illustrative cluster of $n = 9$ locations, located as illustrated in Fig. 3.

The set-up is motivated by the gridded structure of the underlying data which is available on a 20x20km² scale. The sites l_i $(1 \leq i \leq 9)$ are equally spaced by 100km to each other and a location in central Germany was randomly chosen.[2] The denomination of sites is illustrated by the matrix L:

$$L = \begin{bmatrix} l_1 & l_2 & l_3 \\ l_4 & l_5 & l_6 \\ l_7 & l_8 & l_9 \end{bmatrix} \tag{4}$$

Typically, when no correlation is accounted for, a representative irradiation profile for a certain region is used and applied to the accumulated size of all PV systems within the region. In order to compare to this approach, we assume a PV system with a nominal (peak) power of 90MWp and take the simulated irradiation of l_5 as representative profile for the whole cluster (locations 1-9). In comparison, nine separate 10MWp PV systems with the same technical characteristics are allocated to each location and the simulated site-specific irradiation profile is applied. Then, the generation of the different sites is aggregated to one 90MWp system. For both cases, the same ambient temperature profile, representative for the cluster, is used. The simulation runs on 10 minute time steps and covers a full year.

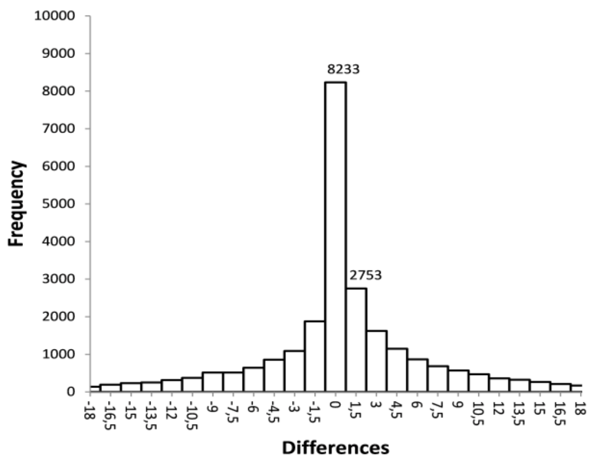

***Fig. 4:** Differences of 10min time steps within a year between one 90MWp (l1) and nine aggregated 10MWp PV systems (irradiation values equal zero are excluded)*

[2] The coordinates of the central location l_5 are +49.81° latitude and +10.17° longitude.

The consideration of local correlation results in different electrical PV supplies. Fig. 4 shows the occurrence frequency of the power difference between both cases. For 8233 time steps of the simulation, the difference is lower than ± 0.75MW, for 2753 time steps, the supply of the 90MWp PV system is 0.75-2.25MW higher than the sum of the nine locations. The slight negative skewness of the distribution is reasoned by a higher irradiation of l_5 compared to the average irradiation of the other locations. That indicates the problem of choosing a “representati e” profile for a region

In the extreme case, there is an underestimation of -51MW. Albeit this event occurs only twice per year, there is a crucial impact for capacity and dispatch planning or grid issues when half of the installed power is not supplied. Bearing in mind the installed capacity of photovoltaics in Germany for example which exceeds 30.000 MW, it becomes clear that ignoring spatial correlation between RES-E generation units might cause high risks for the security of supply.

4. Conclusion and outlook

A methodology to simulate spatially correlated irradiation time series based on copula theory was successfully implemented. Enhanced trend adjustments to the time series and the ability to explain large parts of correlation were presented. Furthermore, we show that for simulating global irradiation, the spatial weather dependencies should be taken into account to generate valid PV profiles. Future enhancements of the simulation process can be reached by an integrated approach which simulates a plurality of parameters including spatial and temporal correlations between the various parameters (e.g. temperature, wind and global irradiation). The methodology to generate spatially correlated PV profiles outlined in this paper can be applied to the analysis of decentralized energy systems and grids.

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